Systemic Insight: The interplay between interactivity, incubation and transfer in insight problem solving

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Abstract

Classical perspectives on problem solving are embedded in computational models of insight problem solving, such as the information-processing model (e.g., Newell & Simon, 1972). Problem-solving activity is viewed as a product of information-processing in which people see or hear problem information, think about the solution, then produce the solution: see or hear, think, then act. More recently, Ohlsson (2011) suggested people solve problems by mentally restructuring the problem information. Hence, insight comes about as a consequence of restructuring (Weisberg, 2014). As such, the origin of insight is commonly understood as a mental experience. However, the traditional frameworks explaining the insight experience commonly overlook the influence of reasoners' immediate environment. Systemic cognition frameworks such as the Extended Mind Thesis (Clark & Chalmers, 1998), Distributed Cognition (Hollan, Hutchins, & Kirsh, 2000) and the Systemic Thinking Model (Vallée-Tourangeau, Abadie, & Vallée-Tourangeau, 2015; Vallée-Tourangeau & Vallée-Tourangeau, 2017) assume information-processing is augmented when spread across mental and physical resources. When presented with a physical representation of a task, making changes to that physical representation, even arbitrary ones, may offer cues to new strategies, enabling better planning and efficiency in progressing towards a goal. Accordingly, the opportunity to interact and coordinate with the immediate environment enhances insight performance.

This thesis sought to explore insight performance from a systemic cognition perspective. The research program investigated how the level of interactivity influenced solution rate in the Cheap Necklace Problem (de Bono, 1967; Silveira, 1971). Across four experiments, participants attempted to solve the problem either in a low interactivity condition, using only pen-and-paper and relying heavily on mental restructuring, or in a high interactivity condition, with a physical model of the problem with constituent elements they

could manipulate while attempting to find a solution. The results across the experiments confirmed that increasing the level of interactivity resulted in enhanced insight performance.

Incubation and transfer are often upheld as key determinants for insight performance. Thus, in addition to exploring the impact of interactivity, the experiments investigated how interactivity may interact with incubation and transfer to promote insight. To measure incubation effects, participants in the first two experiments reattempted the same problem after a two-week break. There was evidence of an incubation effect as performance substantially improved on the subsequent attempt. To explore transfer, a new Cheap Necklace Problem variant was introduced, which participants in the final two experiments attempted following the original version of the problem. Transfer was evident as participants were able to successfully transfer their solution to solve the new variant. Moreover, overall performance improved on the subsequent problem. Across the four experiments, the level of interactivity offered on the second problem attempt was important: When the problem presentation changed (low interactivity to high interactivity or high interactivity to low interactivity) performance only improved when working in a highly interactive task environment second. Thus, insight through interactivity fosters stronger performance on both the initial and subsequent task. This thesis further explored how interactivity prompts insight in a dynamic agent-environment by recording and analysing participants' actions. One important finding from these behavioural analyses was the fact that those who spent the largest proportion of their time reconfiguring the task environment, thus making the most of the malleability of the artefacts available, were also most likely to reach insight.

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Chapter 1: General Introduction

Day-to-day activities bring with them problems of varying nature and complexity. Different strategies are implemented to work these out, which can be based on similar previous encounters, seeking help from others, utilizing information and tools immediately available, and so on. Some problems can be solved routinely, such as completing a jigsaw puzzle, while others require more effort, like discovering a scientific breakthrough. Difficult problems may be solved following a "light bulb" moment, where the problem solver suddenly knows exactly what to do after having been stuck. Anecdotally, while Isaac Newton sat under a tree contemplating the physics of the universe, an apple fell on his head. Suddenly, he had a "Eureka" moment and was able to develop the law of universal gravitation. In 1489, Leonardo da Vinci designed the Aerial Screw, an early version of the helicopter. As with most of his drawings and designs, they were based on observing nature (Weisberg, 2014). Reflecting on the how birds move through the air combined with his familiarity of screws, he inferred that a spiral in the air will rise allowing for human flight. Such apocryphal stories have led some researchers to ask "why is it that some people, when they are faced with problems, get clever ideas, make new inventions and discoveries? What happens, what are the processes that lead to such solutions" (Wertheimer, 1959, quoted in Mayer, 1995, p. 3). Leonardo da Vinci's clever invention was inspired by something he'd already known to create something new. Much like the Thinker, the bronze sculpture by Auguste Rodin (see Figure 1.1), it is assumed the process that leads to such clever ideas, new inventions and discoveries is effortful thinking. Of course, Newton and da Vinci were exceptional masterminds, undoubtedly endowed with great cognitive abilities to think and create. However, it is possible that their mastery also came through an extraordinary ability to utilise information already available in the world to facilitate their thinking and creativity.

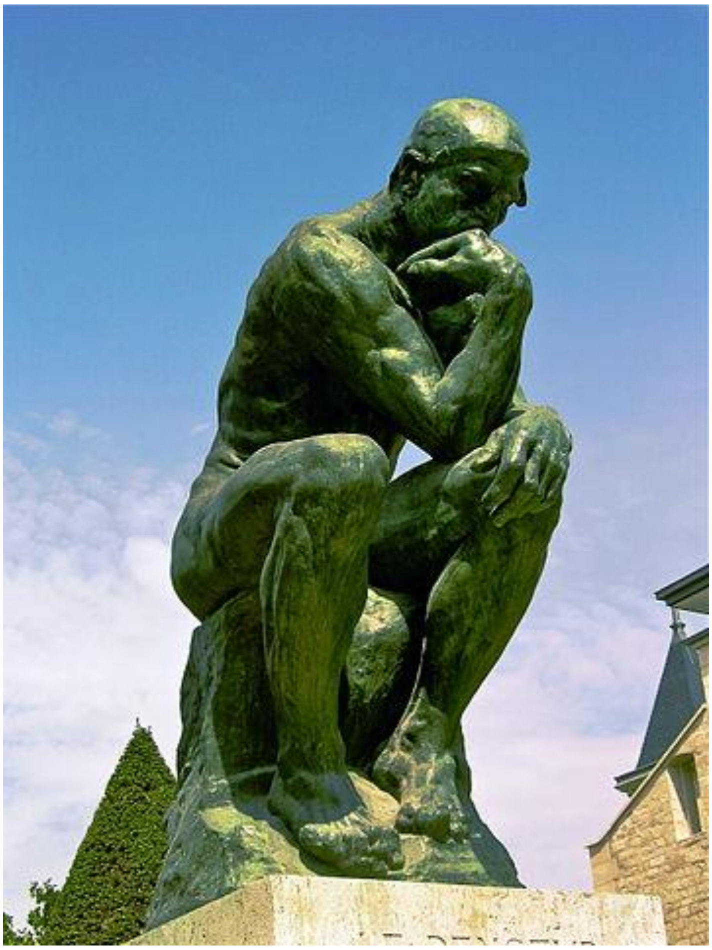

Figure 1.1. Image of “The Thinker”, a bronze sculpture by Auguste Rodin.

The way people find solutions and breakthroughs to problems they face helps better understand the mechanics of human cognition. Problem solving is an important function of cognition, which is assumed to involve central executive processing and working memory (Gilhooly, Fioratou, & Henretty, 2010). Problems can either be analytical problems, with well-defined starting position and goal, or insight problems with a misleading initial representation. While analytical problems can always be solved through a series of logical steps, insight problems require a change in the initial representation (Weisberg, 1995). How restructuring the initial representation of the insight problem transpires has challenged cognitive psychologists from early Gestalt psychologists (e.g. Koffka, 1935; Köhler, 1925) to more recent information-processing approaches (e.g., MacGregor, Chronicle, & Ormerod, 2001; Newell & Simon, 1972; Ohlsson, 1992, 2011). Insightful solutions are identifiable when they occur, but what occurs during the insight process remains a mystery (Walinga, 2011).

Historically, the information-processing model has been a cornerstone of cognitive psychology. The information-processing model equates the way a computer processes information to that of human thinking and cognition (e.g., Newell & Simon, 1972; Newell, Shaw & Simon, 1958; Simon, 1996). As a computer manipulates and processes information to generate outputs, the brain too manipulates and processes information to produce ideas and actions (Simon, 1996). Thus, behaviour is an output of mental information-processing; we see or hear, think, then act. Accordingly, problems are solved by the mental restructuring and processing, which in turn produces a suitable solution. The individual's cognitive ability, such as their knowledge, long-term memory, and attention are largely responsible for a solution (Baddeley, 2012). Therefore, solutions are subject to the individual problem solver and his or her mental capacity and working memory (Chein, Weisberg, Streeter, & Kwok, 2010; Weisberg, 2015).

Contrasting with this established view, Hutchins (1995) detailed an ecological study of USS Palau, a US naval ship, capturing the various ways crew members solve various problems and handled information-processing activity in the book 'Cognition in the Wild.' The successful navigation of the naval ship was contingent upon interactions among the crew and awareness of a constantly changing environment, which altered mental representations. Cognitively demanding tasks, such as attempting to stop the ship before reaching a bridge, were performed through interacting with other crew members, never in isolation. Cognition was not observed as an individual mental process, but rather as a process of acting on the world and a "social distribution of cognitive labour" (Hutchins, 1995, p. 228). A single crew member was unlikely to stop the ship or navigate it to port: It was the result of the interactions of all the crew members as a coordinated dynamic distributed system. In a similar vein, there has been growing scrutiny rejecting internal information-processing models of cognition as a representation of cognitive activity by philosophers (e.g., Clark & Chalmers, 1998) and more recently cognitive psychologists (e.g., Vallée-Tourangeau, Abadie, & Vallée-Tourangeau, 2015).

The research reported in this thesis challenges the assumption that successful cognition and information-processing results solely from mental processes. To understand the processes that lead to insightful clever ideas and new discoveries, we must appreciate how thinkers engage with their environment to develop their thoughts. Objects in the environment become an inherent part of a cognitive system, within which extended and distributed information-processing activity enhances people's thinking (Hutchins, 2001). In other words, insight is not only the outcome of mental processes, but instead results from fruitful interactions with one's environment. The programme of research reported in this thesis examined systemic cognition and information-processing activity adopting a critical perspective on the internalist assumption that thinking as a cognitive process occurs exclusively in the brain (Adams & Aizawa, 2010). Four experiments are reported, which examine insight problem solving performance while varying the degree of interactions afforded by the environment. In addition, an in-depth analysis of problem-solving behaviour under a highly interactive environment is also included.

The review of literature was allocated to two chapters. The first literature review, Chapter 2, provides an overview of the historical and traditional accounts of insight, insight problems and the insight process. Next, the chapter explores the determinants of insight through incubation and transfer. Finally, the literature review introduced the Cheap Necklace Problem, the insight problem under investigation in this thesis. The second literature review, Chapter 3, widens the discussion by introducing alternative perspectives to the classical information-processing model to account for how cognition emerges. After reviewing the information-processing model of cognition, this chapter introduces the so-called four E's of cognition, that is, cognition as embodied, enacted, embedded (Chemero, 2009; Gallagher, 2008; Varela, Thompson, & Rosch, 1991) and the extended mind thesis (Clark & Chalmers, 1998). Next, the distributed cognition framework (Hutchins, 1995; Hollan, Hutchins, & Kirsh, 2000) is discussed. In the final part of this chapter, the growing experimental literature on interactivity and problem solving is reviewed. Finally, the chapter introduces the systemic thinking model (Vallée-Tourangeau et al., 2015; Vallée-Tourangeau & Vallée-Tourangeau, 2017) as a potential theoretical and methodological framework to further explore the role of interactivity in cognitive performance.

The empirical evidence is introduced in Chapters 4 and 5 with a series of four experiments exploring how interactivity impacts insight in problem solving. Using the Cheap Necklace Problem (CNP, de Bono, 1967; Silveira, 1971), these experiments examine how limiting or increasing the possibilities to interact with the material environment while solving problems has an impact on the rate of insightful solutions. Across the four experiments, the level of interactivity afforded was manipulated and participants attempted to solve the problem either in a low interactivity condition, involving a paper-and-pen "abstract" version of the problem or a high interactivity condition, where participants were able to physically manipulate the elements of the problem. The experiments further explored the commonly studied determinants of insight and whether interactivity would moderate their effect. Experiments 1 and 2 presented in Chapter 4 examined whether the level of interactivity afforded would moderate incubation effects in the CNP. In Experiment 1, participants worked on the CNP in either a low interactivity condition or a high interactivity condition. Following a two-week incubation period, they reattempted the problem with the same level of interactivity as their initial attempt. Experiment 2 used a similar set-up, however, the level of interactivity afforded was altered following the incubation period; those who started with a high level of interactivity reattempted the CNP with a low interactivity level and vice versa.

Experiments 3 and 4 presented in Chapter 5 explored the role of interactivity and transfer in the CNP by introducing a new problem variant of the CNP after participants attempted to complete the first CNP. In Experiment 3, participants attempted both versions of the problem with the same level of interactivity (either low interactivity or high interactivity). In Experiment 4, participants experienced both levels of interactivity, either by working on the first problem in a low interactivity condition and working on the new variant in a high interactivity condition or vice versa.

Chapters 4 and 5 established the impact of interactivity on insight performance, incubation and transfer. Yet, they offer little opportunity to understand how and why interactivity matters. To address this issue, Chapter 6 offers a detailed quantitative and qualitative behavioural analysis of observed interactions during the problem-solving trajectory. Using video-based evidence, this chapter explores how interacting with the environment augments cognition. The chapter begins with a first move analysis. Informed by the criterion for satisfactory progress theory (MacGregor et al., 2001), the first move performed by participants is assessed as a potential predictor of insightful performance. Next, a comparative behavioural analysis is conducted to explore the types of activities taking place while participants interact with the material environment. The total duration and proportion of time during which participants engaged in specific activities was compared in an attempt to identify which types of activity are predictive of successful performance. Lastly, the chapter reports a detailed cognitive event analysis (Steffensen, 2013; Steffensen, Vallée-Tourangeau & Vallée-Tourangeau, 2016) of the entire cognitive trajectory of a single successful solver, with the objective of identifying the particular events and specific interactions that lead to her insightful solution.

Chapter 7 provides an overview of the contributions to knowledge brought about by this programme of research through a synthesis of the experimental findings and behavioural analyses. In a nutshell, it establishes that insight through physical processing fosters stronger performance on a subsequent task, whether the subsequent task is identical or a new variant and whether or not its physical processing affordances are constrained or not via the manipulation of interactivity levels. Moreover, the unique behavioural analyses further emphasis the systemic nature of the emergence of insight and cognition. The chapter concludes with a discussion of methodological and theoretical observations arising from this research programme. Again, clever ideas are not just an outcome of effortful thinking, but meaningful interactions with our environment.

Chapter 2: Insight and Insight Problem Solving

"After reading this book, one may be a bit perplexed about exactly what insight means"

- Sternberg & Davidson (1995, p. 560)

Imagine you are in a dark room with a candle, a book of matches and a box of pins. How can you use these materials to mount a candle on the wall and light up the room? The solution to Duncker's (1945) well-known candlestick problem requires insight, as the obvious solution of sticking the candle to the wall will not allow the candle to burn properly. Instead, successful solvers will need to reject prior knowledge and change their representation of the box containing the pins from container to candle holder. This will allow them to "see" that the box can be pinned to the wall, with the candle mounted on it.

The study of how people (and animals) reach insight has a long history, beginning with early Gestalt psychologists (e.g., Koffka, 1935; Köhler, 1925; Wertheimer, 1959). In a famous study, Köhler (1925) observed hungry chimpanzees trying to fetch bananas outside of their reach. Most notably, Köhler (1925) described taking Sultan, a chimpanzee, into a closed room where bananas were hanging from the ceiling. Sultan was given two sticks, neither of which was long enough to reach the banana. At first, Sultan used either stick on its own in an attempt to reach the banana. After several unsuccessful attempts, he appeared to give up and started playing with the sticks until he accidentally touched the banana by pushing one stick with the other. Following this "incident", he joined the two sticks together and used them as a tool to grab the banana. On subsequent days, he appeared to join the sticks purposefully and immediately reached the banana (Köhler, 1925). Köhler concluded that Sultan had mentally solved the problem before acting out his solution. The sudden transition of knowing how to reach the banana, having previously been unware of what to do, was referred to as insight. This sudden burst of insight is often associated with the “Aha!” experience (Mayer, 1995). Insight is unpredictable and seems to take the problem solver by surprise (Maier, 1931; Metcalfe, 1986; Metcalfe & Wiebe, 1987; Seifert, Meyer, Davidson, Patalano, & Yaniv, 1995).

There are three main components of insight; *the experience of insight, insight problems* and *the insight process*. The insight experience involves deep understanding and sudden awareness of the solution. It is associated with the “Aha!” moment and is typically explored in controlled experiments by psychologists. Insight problems are difficult problems that are usually thought to be solved through an insight experience rather than by a step-by-step procedure. The insight process explores how insight occurs through solving insight problems, or creative breakthroughs. How insight occurs is contentious with opposing theories offering different explanations for the insight process. The current chapter will begin by defining insight and insight problems. Then, the insight process and the main views on how insight comes about will be explored. Next, I will review the determinants of insight with an aim to better understand if, and how, insight can be promoted. Lastly, I will introduce the Cheap Necklace Problem (CNP) as this was the particular insight problem studied in this thesis.

The Experience of Insight

The experience of insight is a phenomenon that is difficult to explain. It may or may not involve a clear subjective “Aha!” experience and can be associated with some restructuring of the problem’s mental representation (Fleck & Weisberg, 2013). Table 2.1 summarises different definitions for the insight experience provided by different key scholars who have studied it.

Table 2.1.

Definitions of insight

Definition	Author
"Insight occurs when a solver restructures a previously intractable problem such that a new understanding of what needs to be done appears in consciousness"	Ansburg, 2000, p. 143
"An insight is typically said to occur when an individual is exposed to some new information that results in a new way of looking at a known problem or phenomenon in such a way that its essential features are grasped"	Csikzentmihalyi & Sawyer, 1995, p. 329
"Characterized as a form of understanding (of a problem and its solution) that can result from restructuring, a change in a person's perception of a problem solution"	Dominowski & Dallob, 1995, p. 33
"Insights are the "Aha!" moments in which a new and more effective representation of a problem suddenly bursts into conscious awareness"	Jarman, 2016, p. 21
"Insight is a sudden realization of a problem's solution"	Köhler (1956), quoted in Davidson, 1995, p. 147
"The sudden appearance of the new gestalt, that is, the solution, is the process of reasoning. How and why it comes is not explained. It is like perception: certain elements which one minute are one unity suddenly become an altogether different unity"	Maier, 1930, p. 116
"The process by which a problem solver suddenly moves from a state of not knowing how to solve a problem to a state of knowing how to solve it"	Mayer, 1995, p. 3
"Insightful problem solving occurs when a solver initially fails to solve a problem for which he has requisite knowledge, but eventually successfully solves that problem… Insight occurs in the context of an impasse, which is unmerited in the sense that the thinker is, in fact, competent to solve the problem"	Ohlsson, 1992, p. 4
"…mental events in which new ideas come to mind"	Ohlsson, 2011, p. 87
"A sudden change from not knowing a problem's solution to knowing it consciously"	Siegler, 2000, p. 79
"Insight occurs when a problem is solved through restructuring. That is, if we compare the initial solution attempt(s) with the insightful solution, they must be the result of different analyses of the problem"	Weisberg, 1995, p. 163
"Achieving understanding into a problem and which sometimes comes about suddenly, in an Aha! or Eureka! Experience"	Weisberg, 2015, p. 6

Evidently, key insight researchers have not reached a consensus in defining what insight is. There are, however, some features shared between the definitions. Insight is *sudden* (e.g., Jarman, 2016; Köhler, 1956; Maier, 1930; Mayer, 1995; Siegler, 2000; Weisberg, 2014), insight is associated with *restructuring* (e.g., Ohlsson, 1992, 2011; Weisberg, 1995), and insight is a *new perception* or a *new understanding* (e.g., Ansburg, 2000; Csikzentmihalyi & Sawyer, 2014; Domiowski & Dallob, 1995). Therefore, accepting the "Aha!" experience as a definition is insufficient to encapsulate the phenomenological characteristic of insight (Weisberg, 2014). Moreover, the experience of insight is closely related to the specific types of problems which are solved through insight. These problems are examined in the next section.

Insight Problems

Insight is typically explored in the context of solving problems, which is the process of navigating towards a solution without an obvious path to do so (Mayer, 1992). Problem solvers navigate through a problem space, which encompasses the original problem presented (the initial state), the solution (the goal state), and the operators that can be applied to transform the problem from its initial state to its goal state (Newell & Simon, 1972; Öllinger & Knoblich, 2009). A problem solver is presented with an initial state, such as mixed puzzle pieces, and required to reach a goal, the complete puzzle. This process of moving from the initial state towards the goal is largely unguided. The main component for solving the problem is to understand what the problem actually requires of you, and to discover a suitable way in which to do so (Dominowski & Dallob, 1995). According to the problem space theory, the search is not a trial-and-error of random moves. Rather, problem solvers apply rules to constrain the problem space, making the goal directed search more efficient (Newell & Simon, 1972).

Problems are classified into two broad categories; analytical problems and insight problems. Analytical problems have a clearly specified and well-defined goal, which can be completed through a sequence of steps (Weisberg, 1995), such as putting together the pieces of a puzzle. The solver knows what to do, although may not know how to do so. A classic example of an analytical problem is the Tower of Hanoi task. The problem consists of three pegs and multiple discs increasing in size, which are able to slide onto pegs (see Figure 2.1). Initially, the discs are stacked in size order, with the largest disc at the bottom on the leftmost peg. Problem solvers are required to move the entire stack of discs onto the rightmost peg with the largest disc remaining at the bottom. The aim is to move the discs from left to right in as few moves as possible while only moving one disc at a time. A disc can only be placed on top of one that is larger. The task can be made more difficult by introducing more discs at the beginning of the problem. Even though it may increase in difficulty, the Tower of Hanoi can always be solved in a series of logical moves (Simon, 1975). Analytical problems can often be performed using algorithms that describe a clear path to solution. The "Aha!" experience does not accompany their solution as insight is not experienced or required (Fleck & Weisberg, 2004; Perkins, 1981).

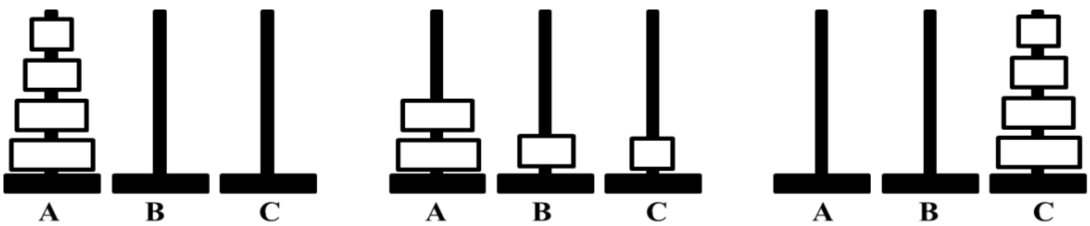

Figure 2.1. The Tower of Hanoi task as initially presented to problem solvers (left), after moving some discs (middle) and once completed (right).

Insight problems, by contrast, are particularly challenging as many irrelevant features of the problem are incorporated into the initial representation, and some more essential features are ignored (Kaplan & Simon, 1990; Öllinger & Knoblich, 2009). Unlike analytical problems, insight problems often lack clear direction and are unsolvable by simple logic or sequential algorithms (Hélie & Sun, 2010). More generally, insight problems are those where the goal state is not immediately obvious to the solver. The initial state does not easily produce a goal state (Gilhooly et al., 2010). In other words, insight problems have no instantly noticeable path to solution, or "effective operators" to apply towards the goal as they are designed to be misleading (Vallée-Tourangeau, Steffensen, Vallée-Tourangeau & Sirota, 2016, p. 195). Instead, the path to solution requires restructuring that is, altering the initial representation of the problem in order to create a new path to solution (Fleck & Weisberg, 2004; Ohlsson, 1992, 2011). There are three specific criteria for insight problem solving. These key characteristics are as follows:

(i) the problem is not routine so previous experience is not important and often ought to be rejected to allow each problem to be faced on its merits (Köhler, 1925, 1959). Insight problems are unique; what the problem actually requires of the solver is not what the solver would normally do.

(ii) the solution requires productive and creative thinking, not reproduction of information in memory. In other words, insight problems are not like memory tests, or arithmetic tests that require good knowledge.

(iii) interpreting what the problem actually requires of the solver is essential (Mayer, 1995). Insight problems are often not about what the solver initially thinks they are about. Although solvers may initially feel they know how to solve the problem, their feelings are often inaccurate and misleading (Metcalfe, 1986).

The nine-dot problem is an example of the misleading nature of insight problems. Used by several researchers (e.g., Lung & Dominowski, 1985; MacGregor et al., 2001; Maier, 1930), the problem presents a 3 × 3 array of dots that all need to be crossed out by drawing four connecting straight lines without taking the pen off the page (see Figure 2.2).

The insightful solution is to draw a line that extends beyond the box, which is not intuitive for most novice problem solvers. The nine-dot problem is a classic example that demonstrates the main difficulty of insight problems; the initial presentation of the problem does not easily produce the desired goal (Gilhooly et al., 2010). The solver's initial representation needs to be changed so he or she does not fixate on the nine-dots as a box, which is common (Dominowski & Dallob, 1995; Weisberg & Alba, 1981).

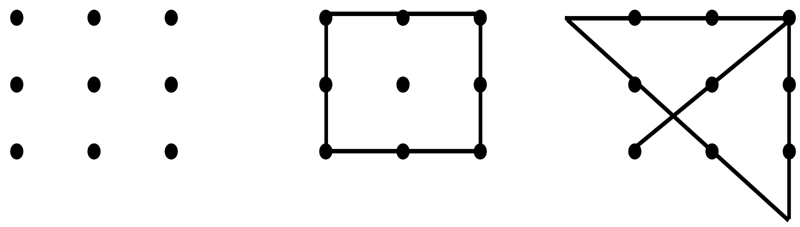

Figure 2.2. The nine-dot problem as initially presented to problem solvers (left), the box problem solvers often create (middle) and the correct solution (left).

Another example is the Matchstick Algebra problem by Knoblich, Ohlsson, Haider and Rhenius (1999). People are presented with arithmetic problems containing false arithmetic expressions written with Roman numerals. They are required to move a single matchstick in a way that would make the false arithmetic expression true (e.g., "VI = VII + I" is made true by moving one matchstick from "VII" to "VI" to produce the correct equation "VII = VI + I"). There are four types of matchstick equations (A to D), which increase in complexity and difficulty. The easiest Type A problems require moving a matchstick between numerals, as in the example given above. Type B solutions require moving a matchstick between a numeral and an operator. For example, I = II **+** II becomes I = II**I** **–** II by moving the vertical matchstick from the + sign to the first II numeral. Type C require problem solvers to transform an operator, where III = III **+** III becomes III = III **=** III. Finally, Type D problems are solvable by creating a perceptual change to one Roman numeral. For example, solvers need to transform X into V to solve XI = III + III, which then becomes **V**I = III + III.

Insight results from the change in representation that leads to the solution. Solvers restricting themselves to drawing lines that fit within the parameters of a box in the 9-dot problem (MacGregor et al., 2001) or those failing to overcome the initial percept in Type D matchstick problems (Knoblich et al., 1999) are hindered by previous experience (Luchins, 1942). By contrast, ignoring pre-existing knowledge and facing the problem on its own merit can prompt a solution.

Insight problems, such as the nine-dot or the candlestick problems, are often thought to be solved following the experience of an “Aha!” moment (Smith, 1995). Accordingly, solutions require a sudden insight (Öllinger, Jones & Knoblich, 2008). Weisberg (1995) criticised this view, however, and instead argued that insight problem may not all require a sudden “Aha!” experience of insight to be solved. He categorised insight problems as Brainteasers and riddles, geometrical, manipulative, and mathematical (Weisberg, 1995). Brainteasers and riddles can be solved by dissolving ambiguity and applying a correct interpretation for the words in the problem. For example, imagine you are told a basketball team won 72-49, but not one man on the team scored a single point. The solution requires overcoming the immediate interpretation of the abstruse phrase “not one man on the team” (i.e., no-one on the team or more than one man on the team) and instead find a non-dominant interpretation to realise women can play basketball also. Geometrical problems are those that require altering elements of the initial state in order to produce the goal, like the nine-dot problem. The solution to geometrical problems comes about through altering problem elements and restructuring. Manipulative problems, such as the candlestick problem, are often solved through the uncharacteristic use of problem characters; using a box as a stand, not a container. Lastly, mathematical problems are solved through altering the way a problem is thought of. Take the sock problem, where there are single black and brown socks in a drawer in 5:4 ratio; the problem asks solvers how many socks they need to take out of the drawer before getting a matching pair. The solution requires ignoring the ratio information as picking up three socks will give two of the same colour sock. Table 2.2 provides detailed examples of the four types of insight problems identified by Weisberg (1995).

Table 2.2

The four taxonomies of insight problems with examples adapted from Weisberg (1995, p. 184).

Brainteasers and Riddles
Animals in pens (17A). Describe how you could put 17 animals into four pens so that there is an odd number of animals in each pen. (Metcalfe, 1986 using 27 animals; Vallée-Tourangeau, Steffensen, Vallée-Tourangeau & Sirota, 2016)
Solution: Make four overlapping pens and put all 17 animals in the centre pen.
Marrying man: A man in a town married 20 women in the town. He and the women are still alive, and he has had no divorces. He is not a bigamist and is not a Mormon and yet he broke no law. How is that possible? (Gardner, 1978)
Solution: The man is a minister who married the women to their husbands.
Geometrical Problems
Necklace: You are given four separate pieces of chain that are each three links in length. It costs 2 cents to open a link and 3 cents to close a link. All the links are closed at the beginning of the problem. Your goal is to join all 12 links of chain into a single circle at a cost of no more than 15 cents (Metcalfe, 1986; Silveira, 1971; Wicklegren, 1974).
Solution: Break up a single three-link piece and use its links to attach the remaining three chains.
Nine dot: Without lifting your pencil from the paper, connect the nine dots by drawing four straight lines (MacGregor, Ormerod & Chronicle, 2001; Maier, 1930; Weisberg & Alba, 1981).
Solution: Draw a line that extends outside the square
Manipulative Problems
Candle: Attach a candle to a door so that it can burn properly. Among available objects are a book of matches and a box of tacks (Duncker, 1945; Glucksberg & Weisberg, 1966; Weisberg & Suls, 1973)
Solution: Use the box from the tacks as a candle holder or shelf
Two strings: Two strings are hanging from the ceiling, far enough apart that it is impossible to grasp the second string while holding the first. Among the items in the room are a chair and a table on which lay the following objects: a screwdriver and a piece of string (Maier, 1931).
Solution: Attach the screwdriver to one of the strings to create a pendulum. While grabbing the other string, grab the string with the screwdriver attached on the upward swing.
Mathematical Problems
Socks: If you have black socks and brown socks in your drawer, mixed in the ratio of 4:5, how many socks will you have to take out to be sure of having a pair the same colour? (Sternberg & Davidson, 1982)
Solution: By withdrawing three socks, you have a pair, either black or brown (the ratio is irrelevant).
Water lilies: Water lilies double in area every 24 hours. At the beginning of the summer, there is one water lily on the lake. It takes 60 days for the lake to become completely covered with water lilies. On what day is the lake half covered? (Fredrick, 2005; Sternberg & Davidson, 1982)
Solution: On day 59.

The commonality among the problem types in Table 2.2 is that the first response given by the solver is usually incorrect. Even though the solutions to these problems elicit a contrasting set of processes, these problems are not well-defined, thus determined to be insight problems (Weisberg, 1995). The problems may be “pure”, which are solved by insight alone and discontinuity of normal thinking or “hybrid” of insight and trial-and-error (Weisberg, 1995). The presence or absence of insight resides in the solver’s solution, rather than in the problem (Bowden & Jung-Beeman, 2007, p. 88). For a solution to be considered insightful, therefore, it is contingent upon finding a solution to a problem that the researcher has deemed an insight problem.

The Insight Process

Insight is identifiable when it happens; what occurs during the insight process remains a mystery (Walinga, 2011). Insight and insightful solutions are idiosyncratic: some problem solvers may incrementally produce a solution following a series of steps while others gain a sudden burst of awareness (Chu & MacGregor, 2011). The Gestalt psychologists proposed that the insight process unfolds in one of two ways; through unexpected awareness or through reproductive thinking. Broadly, the burst of awareness is achieved through the sudden realisation of what the problem requires, putting aside pre-existing knowledge, and attending to the problem as unique (Weisberg, 2015; Wertheimer, 1959). This perspective is referred to as a *special-process*, distinct from regular thinking (Bowden, Jung-Beeman, Fleck & Kounios, 2005). Alternately, reproductive thinking is applying pre-existing knowledge and information onto a newly faced problem. As knowledge is pre-existing, a sequential process of conscious steps allows for incremental progress, which can be assessed by how close to the solution one feels (Fleck & Weisberg, 2013; Metcalfe, 1986; Metcalfe & Wiebe, 1987). This perspective is referred to as *business-as-usual* due to the routine nature of insightful attainment (Bowden et al., 2005).

Special-process

The special-process view of insight is that it emerges in the context of an impasse (Ohlsson, 1992). The impasse, a mental block in which a problem solver is stuck, is broken through sudden comprehension and awareness. Thus, the occurrence of insight is a sequence that encompasses an impasse. The sequence begins with a search, then an impasse, followed by insight and a subsequent aftermath (Ohlsson, 2011). The problem solver begins by exploring the problem to develop an understanding of the goal. The problem solver may try some solutions based on previous experience that appear to support steady progress towards the goal (i.e., search). After attempting all known possibilities, they may find themselves unaware of how to progress (i.e. impasse). If the impasse is “warranted” by the problem solvers’ lack of competence or knowledge, failure is inevitable (Ohlsson, 2011, p. 91). However, if the impasse is “unwarranted” in that the problem solver possesses the necessary competence and knowledge, persistent effort may lead to insight. Insight is not guaranteed, but should it occur, it is an unconscious process, a “mental event”. Once insight is achieved, the problem solver may quickly navigate towards the correct solution or may still need to consider further steps to achieve the solution. In some instance, they may fail to apply the insightful knowledge effectively, failing to achieve the solution. Insight comes about as a consequence of restructuring following an impasse, with the insight permitting the development of a solution (Weisberg, 2014). Restructuring is an unconscious process (Ohlsson, 2011). The *insight sequence* (Fleck & Weisberg, 2004, 2013; Ohlsson, 1992, 2011; Weisberg, 2014), which is a linear process of reaching a solution following insight after incubation, is as follows;

“attempts solution → consistent failure → impasse → restructuring → Aha! → solution.”

The representational change theory (RCT) and the redistribution theory presented by Ohlsson (1992, 2011) have largely influenced the discussion of how an impasse is broken. According to RCT, problem solvers ought to create new mental representations of the problem in order to achieve insight. Restructuring the problem occurs through one of three ways: elaboration, re-encoding and constraint relaxation. Elaboration probes the solver to re-examine the task in order to assess if there was anything overlooked that could be useful for the solution. In re-encoding, pre-existing objects are reconsidered in a different form to trigger new possibilities; the representation of objects change. Constraint relaxation occurs when the representation of the goal changes. This process relies on the competence and knowledge of the problem solver, resulting in a heavy cognitive load (Ohlsson, 2011). Therefore, these representational changes do not parallel any changes in behaviour. Redistribution theory suggests that situations requiring insight initially trigger known possible solutions, which are usually inappropriate. Attempting to use pre-existing information consistently fails to lead to a solution. Repeated failures lead to a process of successive refinement until no further possibilities remain. Inevitably, an impasse is reached, requiring a change in perspective of the problem representation. As the representation changes, new possibilities emerge. Therefore, new ideas emerge through the rejection of past ideas.

A supporting view of insight as a special-process is the notion that the creative processes involved in insight lead to a breakthrough. Insight problems and creative thinking generally are difficult due to their “unreasonable” nature (Perkins, 2000, p. 23), where the problem does not easily lend itself to a solution. In order to advance, a breakthrough in the way we think is required. The *breakthrough sequence* (Perkins, 1981, 2000), which is a sequential process of having a breakthrough by making a significant detachment from the past, is as follows;

"long search → little apparent progress → precipitating event → cognitive snap → transformation"

The solver begins the creative process by searching and attempting as many solutions as possible. Due to the lack of apparent progress made through the long search, the solver reaches an impasse. Then, a mental or external event takes place, resulting in a change of the solver's perspective. Subsequently, a cognitive snap is the moment of insight, or the "Aha!" experience. This leads to a breakthrough; a transformation of the solver's experience of the problem following the insight. In line with Gestalt psychologists' views, the concept of breakthrough thinking by Perkins suggests the creative thinking required for insight demands putting aside pre-existing knowledge and attending to the problem as unique instance. As problems are unreasonable, a solver must approach problems in an unreasonable way. That is to withstand reason, especially that of prior knowledge and previous experience. Consequently, the representation and perspective of the problem must be changed. According to Perkins (2000), restructuring occurs through one of four ways: roving, detecting, reframing, or decentring. Roving entails exploring a wide range of possibilities in order to avoid constraints the solver has self-imposed. Solvers may also restructure through detecting, which is scrutinizing and digging-deep by re-examining the problem, detecting anything that he or she previously overlooked. Reframing is restructuring by developing new ways to frame the problem and frame the solver's understanding. Decentring is letting go of failing strategies, resetting and trying again with new approaches and a new understanding.

Perkin's breakthrough thinking theory is wider ranging than the Gestalt psychologists: the operations of breakthrough thinking attempts to account for the insight experience in both solving insight problems and creative breakthroughs (e.g., da Vinci Aerial Screw design), whereas the Gestalt psychologist have limited their focus to solving insight problems (Weisberg, 2014). However, it is not an entirely unique explanation of insight. There are several similarities and overlaps with the early RCT and more recent Redistribution theory by Ohlsson (1992, 2011). The four ways described by Perkins which may be used to overcome an impasse strongly mirror the three presented in the RCT. Both can be described simply as letting go of what was already known, reassessing the problem and changing how the problem was viewed. The process in which insight occurs still encapsulates the Gestalt stance: insight emerges through restructuring following an impasse. Thus, insight is something that happens to a solver only if they become stuck. However, solvers may not necessarily need to reach an impasse in order to let go of what they already know, reassess the problem and alter their view. These processes may not be unconscious, and restructuring may be a conscious effort that leads to an insightful breakthrough. Restructuring, and consequently insight, may not be an entirely special-process, as the processes may be a product of analysis. I review this alternative “business-as-usual” conception of insight in the following section.

Business-as-usual

The business-as-usual approach to insight postulates insight does not happen to us through a sequence of unknown, undefined, underlying processes. Nor is insight distinct from the cognitive processes associated with general problem solving, reasoning and planning (Seifert et al., 1995). Insightful solutions come about through a conscious analytical process, with experience and knowledge integral (Fleck & Weisberg, 2004, 2013; MacGregor et al., 2001; Simon & Newell, 1971; Weisberg, 2014, 2015). The problem presentation cues solvers to retrieve relevant information from memory, which is used to guide a solution (Weisberg & Alba, 1981). Therefore, problems are solved because of prior experience and knowledge.

While navigating through the problem space, problem-solving activity is driven by the desired goal, which is often achieved through specific subgoals (Duncker, 1945; Fleck & Weisberg, 2013). As insight problems typically do not have a clearly specified goal, Duncker

(1945) identified the representation of the goal and the subgoals created by the problem solver as essential drivers for insight. The representations can be formulated and reformulated to successively refine the problem space and most effectively reach the goal. For example, when attempting the nine-dot problem, the problem solver initially creates a representation of four lines within the parameters of the nine-dots (i.e., a box). When this doesn't work, the initial representation must be changed until a suitable one emerges. The first failed solution attempt is not an impasse; it provides new information for a problem solver to restructure their representation (Fleck & Weisberg, 2013). In other words, insightful solutions can emerge through analytical thinking and constantly altering representations. Restructuring occurs on the basis of the problem solver's mental representation and memory retrieval (Seifert et al., 1995). Thus, Sultan reaching for the banana was due to a series of conscious attempts that helped solve his problem, not a breakthrough in his thinking. This is not to suggest that restructuring is not important. Instead, restructuring is a conscious process brought about by analysis of the problem, not in response to an impasse (Fleck & Weisberg, 2004). Exploration of the problem information makes it possible to retrieve knowledge available in memory and apply it to the new situation.

The criterion for satisfactory progress theory (CSPT) supports the business-as-usual view of insight (MacGregor et al., 2001). The CSPT suggests task difficulty is explained by solvers' attempts to achieve the maximum amount of apparent progress with each move. MacGregor et al. indicated that problem solvers in the nine-dot problem favour moves that make the most progress towards the goal by attempting to cancel out the most number of dots per move. The difficulty lies in the participants initially appearing to make sufficient progress towards the goal (Chu & MacGregor, 2011). By drawing a first straight line through three dots along the perceived square, sufficient progress seems to be made; a third of the lines have been cancelled out using just a quarter of the lines permitted. The second line drawn also leads to apparent satisfactory progress, but when the third line is drawn, it is evident that the progress does not lead to a solution. It is essential that participants look ahead, which is to imagine the outcome of their moves, prior to making them. Looking ahead would allow them to notice that maximization will not lead to a solution, resulting in an earlier experience of 'criterion failure', which is a failure to make moves that meet the criterion for satisfactory progress. Criterion failure permits the discovery of insightful moves. The 8-coin problem, which asks problem solvers to move two coins in an arrangement of 8-coins so that every coin touches exactly three other (Ormerod, Chronicle, & MacGregor, 2002) found insightful solution were lower if the first move satisfied the criterion for progress, as it did not produce the correct solution.

The distinction between the special-process view and the business-as-usual view may not be as distinct as it appears. Although Ohlsson's insight sequence sheds light on the phenomenon of insight where the occurrence of insight is inexplicable, it is not conclusive: analytical thinking can play a critical role in insight problem solving (Weisberg, 2014). In the same manner, analytical thinking may explain the combining of previous knowledge applied to novel situations but fails to account for the experience associated with insight. This is not to suggest that either view ought to be abandoned, rather, the distinction between the approaches ought to be reconsidered.

Integrated Theory of Insight

The integrated theory of insight (Fleck & Weisberg, 2014; Weisberg, 2004) suggests that an integration of the insight sequence and analytical thinking provides a more rounded approach to explaining insight. The views of insight as a special-process and as business-as-usual independently contributed towards the current understanding of insight but are not mutually exclusive. Consider the CSPT proposed by MacGregor et al. (2001) in which the maximizing heuristic suggests why some problem solvers reach an impasse, a combination with the RCT may better explain how they overcome their impasse (Jones, 2003). The two theories are not opposing, thus, in tandem achieve a holistic understanding of insight and the entire creative process: Why we get stuck and how we overcome it, accounting for the entire insight sequence. An integration, therefore, will go further in providing understanding into the idiosyncratic nature of insight. A continuum of analytic thinking and the “Aha!” experience may better explain the cognitive process underlying insight (Fleck & Weisberg, 2004, 2013).

Fleck and Weisberg (2004) presented an inclusive, integrated view for understanding insight and insight problem solving. When presented with a new problem, the initial attempt usually draws on previous knowledge. If a solution is found through knowledge retrieval, the problem is solved. However, should none be available, a search for new information that yields analysis takes place. If this fails, we abandon transfer, but still engage in analytical thinking. Through a continued analytical tactic, a solution may emerge without an impasse or restructuring, but “Aha!” can be experienced. However, should the analytical process fail to produce a solution, a ‘top-down restructuring’ takes place, where new information that emerges from previous failure may provide a new solution trajectory. This restructuring is driven by feedback from previous failures, not from an impasse. Thus, if a solution is found at this stage, the “Aha!” may be experienced, yet did not emerge out of the context of an impasse. If the top-down restructuring is ineffective, then ‘bottom-up’ restructuring, which is the restructuring that emerges from an impasse (Ohlsson, 1992, 2011), may facilitate in reaching insight. This restructuring is driven by a change in representation.

The integrated view of insight as presented by the continuum of analytical thinking and insight proposed insight can be achieved through analytical thinking, and analytical thinking can produce the “Aha!” experience. Findings by Fleck and Weisberg (2004, 2013) suggest some insightful solutions come about independent of the insight sequence, relying on analytical thinking. Yet, the incremental process following a series of steps independent of the spontaneous restructuring that Gestalt psychologists define as insight is deemed as an insightful solution. This returns to the earlier questions posed of what makes an insight problem: is it the process in which a solution was found, or the researcher prescribing a problem as an insight problem?

Determinants of Insight

The underlying processes that prompt insight are still not completely understood. Researchers who accept the Gestalt perspective of restructuring following an impasse assume that a special-process leads to the moment of insight. By contrast, researchers adopting the business-as-usual perspective take insight as continuity of rational thought. These two schools are not mutually exclusive and may adopt aspects of each approach to truly explain the process of insight (Weisberg, 2014). However, these theories are not adequate in explaining what actually happens when an insight problem is solved, and what prompts insight. Nor do they explain why some people are able to find a solution to a problem where others fail. Consequently, the theories of the insight process reviewed ignore key determinants of successful insight performance. Namely, *incubation* and *transfer*. Insightful solutions occur more frequently following an incubation period, a break in active engagement of the problem at hand (Dijksterhuis, 2004). Additionally, transferring relevant information can facilitate insight (Chen, 2002).

Incubation in Insight Problem Solving

Incubation is commonly reported as sudden and unexpected insight after a failed attempt to solve a problem, which occurs when he or she is not actively engaged in the task (Metcalfe & Wiebe, 1987). The formation of new strategies may require a period where attention is diverted away from a task, namely an incubation period (Ritter & Dijksterhuis, 2014). Anecdotally, one spends time consciously engaged in a task unsuccessfully, steps away from it, and then becomes aware of how to accomplish the task (e.g., Poincaré, 1910). According to Wallas (1926), the creative process associated with problem solving transpires through four different stages; preparation, incubation, illumination and verification. People prepare by acquiring the knowledge required for the task and begin their search for a solution. If a solution is found at this stage, there is no need for the remaining three stages. However, a solution is unlikely as insight problems lack clear direction and are unsolvable by simple logic. Consequently, an impasse is reached. In order to break the impasse, the following stage is an incubation period, where attention is diverted away from the task. This leads to illumination, the occurrence of insight, followed by verification in order to validate its accuracy. Illumination, or inspiration (Gilhooly, 2016) occurs from switching to a new strategy or relaxing inappropriate constraints that were self-imposed (MacGregor et al., 2001). Thus, an incubation period allows for better, more creative attempts at solving the problem, which ultimately break the impasse, leading to an insightful solution.

Research on insight problem solving suggests that withdrawing attention from the problem and its concomitant incorrect representations enhance solution rate when the problem is revisited later (Segal, 2004). During an incubation period, insightful solutions are typically thought to emerge either as a result of continued conscious-work on the task, or unconscious processes (Sio & Ormerod, 2009). The conscious-work hypotheses propose the incubation period allows room for supplementary problem-solving activity, from which suitable insightful solutions arise (Gilhooly, 2015). The incubation period also reduces mental fatigue, allowing for covert problem-solving activity that leads in insightful solutions (Sio & Ormerod, 2009). According to intermittent conscious-work hypothesis, problem solvers intermittently make conscious effort in working on the problem at hand, which leads to easier and quicker solutions when they are later faced with the problem (Seifert et al., 1995; Weisberg, 2006). Thus, insightful solutions from this stance are business-as-usual, with the incubation period extending the time in which to solve the problem. According to this hypothesis, problem solvers benefit from an unfilled incubation period as interpolated tasks undertaken may dampen the incubation effect (Dodds, Ward, & Smith, 2003). However, an incubation effect is observed when the break is filled with unrelated activities, leading some researchers to discount the intermittent conscious-work hypothesis (Gilhooly, Georgiou, & Devery, 2013).

The beneficial forgetting or selective forgetting account states a reduction in misleading ideas during the incubation period facilitate insight where problem solvers forget strategies that were constraining and misleading the search (Storm & Hickman, 2015). Mistaken assumptions related to the problem weaken through forgetting, allowing for a renewed effort when the problem is resumed (Smith, 1995). In other words, instead of returning to the problem from the same place they left it, the incubation period allows a fresh start (Smith & Blankenship, 1991). Thus, when reattempting the problem following an incubation period, a more effective strategy can be implemented. Similarly, the attention withdrawal account proposes the incubation period allows for the removal of misleading assumptions to enable more useful ones (MacGregor et al., 2001). Mental representations of the problem are restructured in a more fitting, congenial manner (Seifert et al., 1995). This allows the individual to exploit external cues and information in a way that best allows for insightful solutions to emerge (Sio & Ormerod, 2009).

The unconscious-work hypothesis presents incubation as mental problem-solving activity, a process that the problem solver is unware of that gradually leads to insightful solutions (Dijksterhuis & Nordgren, 2006). Poincaré (1910) describes his own mathematical creative thinking as sudden inspiration during a seafront holiday while thinking of other things. Although a problem solver is not actively engaged in the task, and may do well in interpolated tasks, there is active unconscious processing taking place. This is why, according to the unconscious work hypothesis, insight frequently occurs when a problem solver is not consciously attempting the problem. The incubation period elicits new knowledge, where activation will spread towards previously ignored yet relevant information. The unconscious thoughts being processed during incubation uphold the following aspects: are parallel, bottom-up, inexact and divergent (Dijksterhuis & Nordgren, 2006). By contrast, conscious thoughts are serial, exact and convergent (Ball & Thompson, 2017).

Conscious-work and unconscious-work accounts of incubation formulate different predictions of what happens during an incubation period. Unconscious-work accounts would require attention to be completely shifted from the task in which mental efforts on a different task will free up unconscious process for special-process insight. By contrast, conscious-work does not require filled incubation periods, as problem solvers can continue working on the problem during the incubation period. The theoretical description of incubation by Wallas (1926), which was based on Poincaré's (1910) description, have been tested by several psychology experiments to measure for incubation effects, which support the benefit of setting a problem aside for a time. Under laboratory conditions, the standard experimental paradigm of incubation research compares performance between two groups; a control group and an incubation group (e.g., Patrick, 1986; Segal, 2004; Gilhooly et al., 2009; Silveira, 1971). Participants in a control group work on the problem continuously. By contrast, the incubation group work on the same problem for some time (preparation period), then are asked to stop and given an interpolated task to complete (incubation period), subsequently returning to work on the original problem (post-incubation period). The time spent working on the task during the preparation period and post-incubation period is equal to the time continuously spent in the control group. The interpolated tasks place either a high or low load on cognitive demands.

The incubation effect is measured by solution rates in insight problems, such as the insight problems described previously, or divergent thinking problems, in which many novel and useful creations are generated (Gilhooly, 2016). A typical divergent thinking problem is an alternative-use task, such as asking participants to consider as many creative alternatives for a brick, coat hanger, or any other object (Guildford, 1967; Gilhooly, Fioratou, Anthony, & Wynn, 2007). For example, Gilhooly et al., (2013) used alternative-use task and a creative-mental synthesis tasks to explore the impact of incubation on creative insight. Participants either completed an alternative use task (i.e., noting as many possible alternative uses for a brick) or a creative mental synthesis task (i.e., arrange recognizable patterns from stimuli presented to them) for a 10-minute period. The incubation group were interrupted for 5-minutes to completed interpolated task halfway through. The incubation period enhanced performance in both tasks. There was similar number of responses in the initial five minutes (pre-incubation) between the control and incubation groups. However, there were significantly more alternate uses following an incubation period. Likewise, participants completing the creative mental synthesis task were aided by the incubation period. Although the incubation group did not produce more creative answers, the break helped participants produce more answers in the same overall time. Thus, incubation enhances performance. Gilhooly et al. told their participants that they would be returning to the same problem after their interruption. As participants were made aware of this, they may have continued to formulate more alternative-uses or recognisable patterns even while working on the interpolated tasks. As such, it is not possible to conclude that the significant difference in number of responses resulted from conscious-work or unconscious-work during the incubation period.

Sio and Ormerod (2009) conducted a meta-analysis to resolve the uncertainties surrounding what takes place during the incubation period. Their meta-analysis of 117 journals reiterated that an incubation period does successfully promote insight and creative problem solving. They discovered six potential moderators of incubation: The interpolated task, length of incubation period, length of preparation period, nature of the problem, the presence of solution-relevant cues, and misleading cues (Sio & Ormerod, 2009, p. 95-96). They reported incubation significantly enhances insight in three types of problems. Specifically, in visual problems such as the Matchstick algebra problems, which only have a single solution. In addition, the length of the preparation period was the main moderator of the incubation effect in these visual problems. The longer problem solvers spent struggling to find a solution before the interpolated break period, the stronger the incubation effect observed. Their findings provide little evidence for the conscious-work hypotheses, instead they suggest that unconscious-work best reflect the processes during an incubation period through activating new knowledge or restructuring representations.

Transfer in Insight Problem Solving

The use of previously acquired knowledge taken from one context or domain to another is called *analogous problem solving* (Chen, 2002). Analogical problem solving requires effectively mapping previously acquired information to a new problem. The influence of pre-existing knowledge to solve a new problem is referred to as *transfer* (Mayer, 1992). This is a powerful tool for cognition as reasoners and problem solvers are able to notice commonalities between underlying structures, relating previous knowledge to a new situation (Day & Goldstone, 2011; Dunbar & Blanchette, 2001; Holyoak & Thagard, 1989). Although adults and children, at times, exhibit an ability to transfer analogous information (e.g., Bassok, 1990; Catrambone, 1996; Gick & Holyoak, 1980; Siegler, 1989), most problem solvers show great difficulty to effectively do so on their own (e.g., Detterman, 1993; Greeno, 1974; Hayes & Simon, 1977; Lave, 1988; Reed, Ernst & Banjeri, 1974).

The ability to transfer analogous information from a source problem to a target one has largely centred on the research by Duncker (1926; 1945) who introduced the Radiation problem as a way of determining the underlying structure for insight. Problem solvers are asked to imagine they are a doctor, and that they have a patient with a malignant tumour in his stomach. It is impossible to operate on the patient, but the patient will die unless the tumour is destroyed. There are rays that can be used to destroy the tumour. At a sufficiently high intensity, the tumour will be destroyed. However, at this intensity, surrounding healthy tissues will also be destroyed. Problem solvers are then asked what type of procedure might be used to destroy the tumour using the rays, while avoiding destroying the healthy tissue. The optimal solution, according to Duncker, is to simultaneously use multiple lower intensity rays from different directions, converging at the tumour. The converging rays will produce enough intensity to destroy the tumour, while being safe for the surrounding healthy tissue. This convergence solution was only offered by two (less than 5%) of his participants when they were permitted to note as many solutions as they possibly could. The Radiation problem is difficult for many novice solvers but could be made easier with some prior information.

In an attempt to foster insight through transfer, Gick and Holyoak (1980; 1983) first presented participants with a “General story” where problem solvers were told a small country had a dictator who was ruling from a fortress, which was in the middle of the country. There were multiple roads leading to it through countryside roads, contained mines. A rebel General wanted to capture the fortress using his entire army, yet the mines would detect any large forces, but fail to detect small bodies of men. In order to prevent his army from harm while still saving the surrounding villages, the army was split into small groups. They went down the different roads, arriving at the fortress at the same time ready to attack. The solutions to both the Radiation problem and General story require a point of convergence to achieve their aim. Knowledge of the General story and the way in which the rebel General avoided causing harm to his army and surrounding villages primed some problem solvers. They could draw analogy and successfully transfer the information to the Radiation problem. However, this spontaneous transfer was limited to just 30%. Providing participants with a hint that the General problem may be useful to their solution raised transfer to 75% generating the optimal convergence solution.

The Radiation problem shares procedural similarities with the General story; the process of creating smaller groups to attack from separate angles. None the less, these procedural similarities were not sufficient as most problem solvers failed to transfer their learnt information. The association between the two stories may be rather unclear in that some problem solvers may not have found a story about a rebel general relevant to a medical problem. However, when the association between the solutions was identified to problem solvers, most people could then transfer what they learnt. For spontaneous transfer to take place, which is transfer of analogous information without a hint, similarities in analogous information from the source are essential. A lack of similarity may hinder problem solvers ability to notice, or even recall, the previous information (Chen, 2002; Gick & Holyoak, 1980; Greeno, 1974; Hinsley, Hayes, & Simon, 1977; Reed et al., 1974; Thorndike & Woodworth, 1901). Therefore, a noticeable overlap between the source and target is essential, which are superficial, structural and procedural (Chen, 2002). Superficial similarity refers to source and target problem sharing enough outward similarity that is prominent. This may be characters and objects that are used in both the source and target problem. These superficialities often aren't relevant for solving the target problem but are important as they allow for similarities to be noticed. Structural similarity indicates resemblance in underlying important elements shared by both problems. These similarities, which are conceptual, guide a solution. Superficial similarities help problem solvers notice potential similarities, yet structural similarities are key for transfer (Gentner, Rattermann, & Forbus, 1993). The source and target problems ought to also possess procedural similarities (Keane, 1987), which is the most important for transfer (Chen, 2002). Procedural similarities signify connections in concrete operations, the actions that are shared between source and target problems. The likeness in process is also essential to performance as it allows for analogous information to be acquired. An important factor affecting transfer is the abstractness of the source information, where the abstractness of a general principle fails to benefit reasoners and problem solving (Chen & Daehler, 2000; Weisberg & Alba, 1981). The Radiation problem shared no superficial similarities with the General story, which may have hindered problem solvers' from relating the two on face value. However, the stories share both structural and procedural similarities. Conceptualising both stories, although dressed differently, as requiring the same process of creating smaller groups to attack from separate angles, was essential for transfer.

A similar mapping process is required to abstract and apply a specific concept (e.g., the army men used several different roads to attack meet at the fortress) to a more general schema (e.g., spreading a force across multiple pathways to converge at the desired destination) (Gick & Holyoak, 1983). While the General story and the Radiation problem share similar solutions, the disparate situations that lack transparent resemblances make it difficult to draw analogous information. A source that helps solve new problems effectively should parallel strongly with the target. Therefore, if an insightful solution has been reached, subsequent problems should also be solved. Examples that share superficial similarity promote transfer most effectively as the connection between the source and target problem is more explicit. Working on examples of algebra problems helps to solve new algebra problems (Chen, 2000; Cooper & Sweller, 1987), with transfer being most evident when problems bear likeness and are meaningfully similar. If the problems are similar enough, a single insightful encounter with a problem is sufficient in removing difficulties in subsequent problems (Knoblich et al., 1999). The Matchstick algebra problems measured transfer between similar concrete examples by presenting incorrect arithmetic expressions in two blocks. Knoblich et al. (1999) presented problems in two blocks, each consisting of six arithmetic expressions. The order of arithmetic expressions was presented randomly. In block one, the more difficult problems were solved less frequently. However, in the second block, there was no effect of difficulty (Knoblich et al., 1999). Further, participants spent less time solving the problem in block two. Thus, performance improved between the blocks, in both frequency to solutions and the speed in which they arrived at these solutions. The amount of transfer was a function of initial difficulty, where the harder Type D problems that required creating a perceptual change, resulted in the largest increase in subsequent solution frequencies. Solving a difficult problem first supports transfer, improving efficiency in later problem solving. Attempting to solve a more difficult problem, self-generating a solution as opposed to just hearing a story, prompted large transfer in the matchstick algebra problem. It could be the source information that requires producing a solution may help participants understand and transfer the important components to the target problem more efficiently.

Several studies report a failure to spontaneously use previously acquired information for subsequent problem solving (e.g., Gick & Holyoak, 1980; 1983; Fioratou, 2005). As participants often fail to generalise source information (Fioratou, Flin, & Glavin, 2010), providing a hint about the source information is helpful for later insightful solution (Fleck & Weisberg, 2004; Lave, 1988). A hint may allow problem solvers to look beyond just superficial similarities and notice the similarities in structure and process. Instead of searching for a novel solution to the target problem, a hint moves problem solvers through the search for similarities quicker, hence a failure to transfer the solution without a hint, may be due to a lack of speed in noticing the similarities (Bowden, 1985). Hints refine the search for a solution. A hint allows for better navigation through the problem space, which houses all the possible solutions to a problem, which leads to transfer. Therefore, uninformed participants require more time to search; investigations into spontaneous transfer ought to allow adequate time for reasoners and problem solvers to notice the similarities and produce a solution (Bowden, 1985; Ormerod et al., 2002). However, when reasoners and problem solvers actively engage in the source problem, hints may no longer be as important for transfer (Fioratou et al., 2010; Knoblich et al., 1999).

The Cheap Necklace Problem

The Cheap Necklace Problem (CNP) has been widely used by problem solving researchers exploring how we solve problems with misleading information (Isaak & Just, 1995). Originally reported as the necklace task to explore lateral thinking (de Bono, 1967), the first rigorous study of performance on the CNP was carried out as part of a doctoral thesis work on incubation by Silveira (1971). In its standard form, the CNP is presented with an image and the following instructions (see Figure 2.3):

> You are given four separate pieces of chain that are each three links in length. It costs 2¢ to open a link and 3¢ to close a link. All the links are closed at the beginning of your problem. Your goal is to join all 12 links of chain into a single circle at a cost of no more than 15¢.

Problem solvers attempting this problem must develop the insightful solution of breaking up one of the three-link chains costing 6¢, to use those individual links to connect the remaining three chains at a cost of 9¢. The solution is rarely produced by naïve problem solvers with successful completion often less than 10% (Chu, Dewald, & Chronicle, 2007; Fioratou & Cowley, 2009; Fioratou et al., 2010; Silveira 1971).

You are given four separate pieces of chain that are each three links in length. It costs 2¢ to open a link and 3¢ to close a link. All the links are closed at the beginning of the problem. Your goal is to join all 12 links of chain into a single circle at a cost of no more than 15¢.

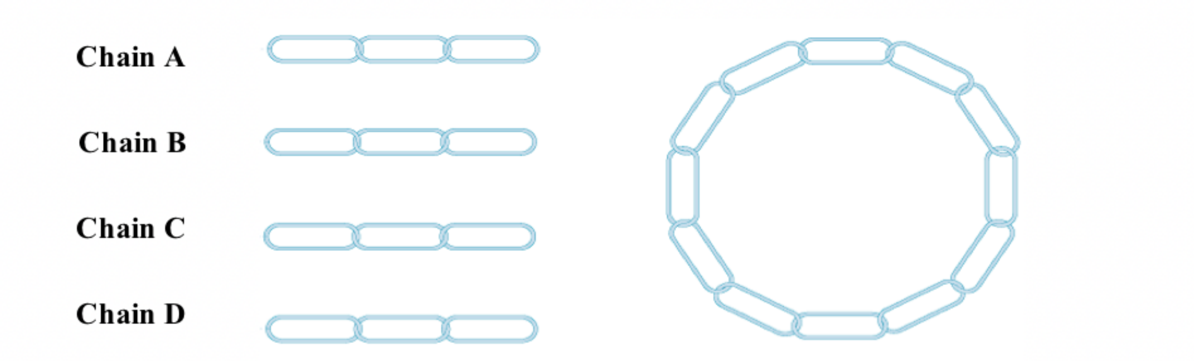

Figure 2.3. The Cheap Necklace Problem as presented to participants by Silveira (1971)

Weisberg's (1995) taxonomy classified the CNP as a hybrid insight problem as solvers can complete the task either with or without restructuring, and solutions can be explained by a special-process or through a process of analysis. In other words, according to Weisberg, problem solvers demonstrate an insightful solution if they suddenly realise they need to use all the links in a single chain to connect the remaining three chains. However, they may also try various different combinations and reach a solution by trial-and-error or deductive thinking (Gilhooly & Murphy, 2005). Thus, the CNP does not assess the underlying cognitive processes for insight, nor does the solution lean exclusively on restructuring or productive thinking.

The CNP is a "multi-property problem" (Fioratou, 2005, p. 13), which includes the following characteristics:

(i) it is assumed to require insight as the solution needs restructuring due to the lack of a clear direction (i.e., "a single circle" can be rather ambiguous) with the problem unsolvable by simple logic or sequential algorithms. However, the CNP has a clearly defined initial state and goal state, which also uniquely qualifies it as an analytical problem (Greeno, 1978).

(ii) it has properties that relate to prior knowledge (i.e., necklaces and opened and closed links are not uncommon to most), which typically misleads problem solvers (Fioratou, 2005)

(iii) it is a multi-step problem that can generate a variety of solution attempts. This makes the solution difficult to reach as problem solvers can move several steps before noticing their error (Chu et al., 2007). Also, the multi-step nature of the CNP allows researchers to analyse the various problem-solving behaviours and paths to solution (Silveira, 1971).

These unique characteristics and nature of the CNP offer an interesting platform from which to investigate insight problem solving.

The Insight Process in the Cheap Necklace Problem

The solution for the CNP requires a detour; breaking a chain before making the necklace. It is not possible to solve this task by simply connecting the ends of each chain, as this will exceed 15¢. Joining the ends of each chain suggests optimal progress towards the goal, as this move costs just 5¢ while making half of the necklace. This path, however, leads to a dead-end as it will eventually cost 20¢. Although it is impossible to solve the CNP with this strategy, participants have been observed to retry it instead of re-evaluating their first move (Chu & MacGregor, 2011). The counterintuitive solution is not obvious; consequently, most participants reach an impasse when attempting the CNP. Participants experiencing an impasse must explore a different path to solution.

According to the RCT, the difficulty in solving the CNP may lie with the representation of the chains as tight perceptual chunks. Prior knowledge determines the problem representation, with the perceptual processes grouping those representations into meaningful chunks to form a representation of the goal. Thus, the representation of the goal constrains how the problem solver searches for a solution (Öllinger, Jones, Faber, &

Knoblich, 2013). Specifically, problem solvers focus on the chains instead of the links. If the tight representation is restructured, insight may be more attainable.

The CSPT assumes that the problem space is too large, so hints may defuse the first obvious move and help reasoners solve the problem (Chu et al., 2007). The application of well-adjusted interchange of different heuristics is a rudimentary component for solving the CNP and other difficult insight problems (Öllinger et al., 2013). Breaking one of the four chains into three separate links is the type of innovative thinking required to solve the problem. Chu et al. (2007, Experiment 1) tested the CSPT account by changing instructions for participants, instructing them to avoid a 6-link chain, and the RCT account by using differing colours in the links of a single chain. Seventy-eight participants were either placed in a control condition, given the CSPT hint, or the RCT hint. All participants had up to 20-minutes to complete the task making any notes on a sheet of paper, stopping only when they found the solution. The control group had the highest rate of 43.5% insight performance, while the only 34.8% in the CSPT hint found the solution, and 39.1% in the RCT hint condition. Chu et al. concluded the lack of significant difference between conditions was either due to the 20-minute time period being too long, or participants simply not believing the hints.

In a second experiment using the same three conditions, 60 participants attempted the CNP in up to 10 trials, where they were asked to restart the problem every 2-minutes, or whenever they spent 15¢. In order to see the participants' trial-by-trial solution attempts, the experimenters used four metal chains made of three "quick fix" links that could be opened and closed by participants screwing and unscrewing them (Chu et al., 2007, Experiment 2). This allowed one-on-one participant observation to determine whether participants followed the hint provided as only measuring solution rates could not ascertain their use and their effect. Again, there was no difference between the three groups; 80% of the control condition successfully completed the task, and 75% of both the CSPT and RCT attaining insight. Even with the hint to avoid maximizing, problem solvers again still attempted to create a 6-link chain as their first move. Chu et al. concluded this may be due to participants' desire to satisfy a criterion is extremely strong, as these participants often persisted with this first move, even when they knew it was wrong. Thus, these hints are ineffective in improving performance. Chu et al. concluded that a mix of hints to prevent selecting the obvious first move, as well as presenting one of the chains made up of different colours would be most effective in improving solution rates: a combination of the two will enhance insightful solution. The instructions may have failed to improve performance as the hint or the representation change was provided for the participant. It could be that the realisation to not maximise and to change the representation of the problem ought to arise from the participant. These findings suggest that both perceptual chunking and criterion for satisfactory progress contribute to the impasse.

Incubation in the Cheap Necklace Problem

Silveira (1971, Experiment 1) investigated the effect of incubation using CNP. She measured whether the problem could become easier if delays were placed between an initial intense period of working on the problem and a subsequent attempt at completing the problem. Participants were shown the CNP on a sheet of paper and given a pencil to work out the solution, as in Figure 2.3. They were free to make notes on the paper while they thought about the problem. They were also made aware that they would be interrupted during their problem solving, though they were not told when and for how long. There were five conditions, one control and four experimental conditions representing the length of the incubation period (short-interruption or long-interruption) and whether the interruption happened early, after 3-minutes of working on the problem, or later after 13-minutes. All participants had 35-minutes in total to work on the task, with only the control group working straight through that time. The short-interruption participants stopped working on the problem for 30-minutes and instructed not to think of the problem during that time. To help them stop thinking about the CNP, they were asked to read a book of their choice for 30-minutes. The short-interruption group resumed working on the CNP after this 30-minute period. The long-interruption group were then asked to leave the lab and return in 3 and half hours, totalling a 4-hour incubation period. Silveira reported 47% of participants in the control group successfully completed the CNP, 45% of participants who had an early short-interruption, and 40% of participants who had an early long interruption. These performance rates increased when participants were interrupted later, with 64% of those with a late short-interruption solving the problem, and 86% in the late long-interruption.

In a subsequent experiment using just the control group and the late long-interruption conditions, Silveira (1971, Experiment 2) explored the impact of the length of the incubation period. Thirteen minutes after reaching an impasse, all participants were interrupted to complete a short questionnaire about their performance. The control group could resume work on the problem as soon as the questionnaire was complete. The experimental groups were cautioned not thinking about the problem during their interruption and if the problem came to mind, they were instructed to think about something else. For 30-minutes, they read books, then were given a 4-hour break before resuming work on the CNP. After this incubation period, they were given the same sheet they had previously been working with and continued searching for a solution. Participants across both conditions performed well in the task, with successful insight performance at 38%, and 81% respectively. The prolonged incubation period vastly benefited solution rates in the CNP, especially when the interruption took place after participants engaged with the problem for a longer period of time.

Transfer in the Cheap Necklace Problem

To explore transfer in the CNP, Fioratou (2005) devised a new variant of the CNP. The new variant consisted of two 4-link chains and two 2-link chains. This new variant required a similar solution of breaking one smaller chain into two links, then using those links to create a complete necklace. However, the new variant was slightly different perceptually, appearing to require an alternate solution. Like the standard CNP, the solution requires opening and closing three links. Unlike the standard CNP, only one 2-link chain needs to be deconstructed and joining the ends of two chains is a permissible move. Over two experiments, both using the standard CNP as the source, the effect of hint was assessed. Participants who had attempted the standard version two-weeks previously, were reminded of the solution. They were placed in one of three conditions; standard CNP, first new variant (4-4-2-2) or the second new variant (4-2-4-2). Participants were shown the version of the CNP they were attempting on a sheet of paper and were free to make notes on the paper while they thought about the problem. They were encouraged to continue to work on the problem for a continuous 10-minutes. Eighty-five percent of participants were able to reproduce the solution to the standard CNP (Fioratou 2005, Experiment 9). However, few participants were able to produce the solution to the new variants of the problem; 33% for the first new variant, 20% for the second new variant. Again, spontaneous transfer was limited, even when these problem solvers were actively engaged in the source problem. Fioratou (2005, Experiment 10) assessed whether giving participants a hint would help them to transfer. Participants attempted the standard CNP, half of them being told "*sometimes it is necessary to destroy in order to create. In solving some problems, you need to go backwards before you can go forwards*." They were all shown the solution prior to being distracted with some filler tasks for 4-minutes. Then, they attempted the 4-4-2-2 CNP variant, with the hint group being told "*information about the first problem you saw may prove useful in solving the next problem*".

The hint did not help participants in either version of the CNP. Although the two variants share superficial, structural and procedural similarities, most participants failed to transfer the solution to the new variant. Fioratou (2005) explains that there may have been due to a tension between conceptual and procedural knowledge; all participants were able to procedurally reproduce the given solution as they'd been shown, yet most failed to gain conceptual insight as they couldn't apply that solution to the new variant (Ormerod et al., 2006). Conceptual insight is an important drive for transfer, which might not be achieved when provided with a solution (as in Fioratou, 2005).

In addition to exploring transfer, Fioratou (2005) aimed to investigate the underlying processes for insight in the CNP by altering the way the problem was presented to participants. Similar to Chu et al. (2007) the colours of some links were changed, and instructions were provided not to connect the ends of chains. To determine the effect that altering the task instruction had on the problem-solving journey, Fioratou (2005, Experiments 2 and 6) observed participants' solution attempts. To do so, a concretised version of the CNP was used, consisting of chains made up of detachable metal links. By providing participants with a concretised version to construct a solution, the task environment was altered. An insightful solutions rate in the concretised version was 69% for naïve participants who were given the hint not to connect the ends of the chain (Experiment 6). This was much higher than the 40% solution observed when the same hint was provided but on pen-and-paper (Experiment 8). Although the improved performance may be explained by the manipulations created in the experiments, Fioratou concludes that this effect was most likely a result of a richer external representation of the problem allowing participants to have clearer understanding of the moves they made. Similarly, the two experiments by Chu et al. (2007) used different problem presentations in each. In the first experiment, participants attempted the CNP on pen-and-paper yet required to construct a solution using metal links in the second. The overall rate of performance nearly doubled in all three conditions across experiments. Although Chu et al. did not remark on this, the increase in performance may be explained by participants being frequently interrupted, forcing them to reassess their strategy often. Alternately, it could be that the metal links acted as a problem-solving tool (Zhang & Norman, 1994). It is not possible to draw a conclusion as to which explanation holds, or any other explanation that may emerge, accounts for the two-fold increase in performance. Taken together with Fioratou's findings, it is likely that the problem presentation, in which the participants were able to enact a solution through a concretised version of the CNP is a more robust description of the higher solution rates.

Often, insight problems are presented with physical props or tools, such as the candle problem (Duncker, 1945), the two-string problem (Maier, 1931), and the eight-coin problem (Ormerod et al., 2002). However, enacting a solution is still considered to be a result of mental restructuring (Fleck & Weisberg, 2013). Objects are able to transform problem solvers approaches to a task, by creating a structure (Baber, 2003; Zhang & Norman, 1994). Although the CNP chains were used to provide visual data for Chu et al. (2007, Experiment 2) and Fioratou (2005, Experiment 6), they may have extended the problem-solver's cognitive capacity when reaching for the goal (Baber, 2003). This is not to suggest that the chains made the participants smarter but enacting a solution may have augmented their cognitive powers. Therefore, the physical construction of a solution may be implicated in insightful performance. The subsequent chapter explores this possibility.

Chapter 3: Systemic Cognition

"One of the most dangerous of ideas for a philosopher is, oddly enough, that we think with our heads or in our heads. The idea of thinking as a process in the head, in a completely enclosed space, gives him something occult."

- *Wittgenstein, Zettel (1967)*

Consider the question "how does cognition happen?" A typical response may be the brain or the head. We remember in our head, we think in our head, so we must come to know in our head also. Likewise, insight and the processes leading to insight are typically believed to be mental events. Take, for example, Sultan, the chimpanzee observed by Köhler as discussed in Chapter 2 (p. 8). His insightful actions aiming to reach a banana are typically considered to have resulted from mental restructuring; he thought, then he did. More generally, whether people are thought to solve insight problems through a 'special-process' or 'business-as-usual', researchers typically agree that insightful solutions result from what happens in our heads; we think, then we solve (e.g., Fleck & Weisberg, 2004, 2013; MacGregor et al., 2001; Seifert et al., 1995; Simon & Newell, 1971; Weisberg, 2014, 2015; Ohlsson, 1992, 2011).

Psychologists and cognitive neuroscientists normally adhere to the notion that knowledge acquisition, understanding and perception are processes which results from neural activity. Some neuroscientists have claimed specific brain areas that activate during problem solving are responsible for insight (Jung-Beeman, Bowden, Haberman, Frymiare, Arambel-Liu, & Greenblatt, 2004; Kounios & Beeman, 2014). However, there is no clear consensus about the neurophysiological source of insight (Sprugnoli et al., 2017). As Chu and McGregor (2011, p. 143) put it: "There is no single major area responsible for all well-defined or insight problem solving, because the complex cognitive functions performed by the brain needs the integration and cooperation of numerous regions to solve a problem".

Even though the brain is typically considered as the power-house of cognition, alternative theoretical perspectives have emerged since the mid-nineties. Specifically, some authors have proposed that behaviour and action should be considered as making a non-trivial contribution to cognition. To return to Sultan, he succeeded by insightfully joining two sticks together, in other words, he used external artefacts to support his problem solving. Internalism, the belief that thinking is a process occurring exclusively in the brain (Adams & Aizawa, 2010), has increasingly been challenged by anthropologists (e.g., Hutchins, 1995) and philosophers (e.g., Clark & Chalmers, 1998), and, more recently, cognitive psychologists (e.g., Vallée-Tourangeau et al., 2015). Although these scholars are united in rejecting a purely internalist conception of cognition, there is no clear consensus as to what an alternative conception may be. Some argue for a radical embodiment view (e.g., Chemero, 2009) while others are more moderate and call for a view of cognition that neither exclusively results from activity in the brain, nor from activity taking place just in the world, but rather from the interaction between both mental and physical activity (Hutchins, 1995; Vallée-Tourangeau et al., 2015).

This present chapter presents cognition as a systemic occurrence; beyond the information-processing model and beyond the brain. It begins by reviewing the information-processing model (Newell & Simon, 1972; Baddeley, 2012) before introducing two prominent theories of cognition beyond the brain; the distributed cognition framework (Hollan, Hutchins, & Kirsh, 2000; Hutchins, 1995), and the extended mind thesis (Clark & Chalmers, 1999). The chapter then concludes with a presentation of the systemic thinking model (Vallée-Tourangeau et al., 2015; Vallée-Tourangeau & Vallée-Tourangeau, 2017).

The Information-Processing Model

The development of computers in the early fifties had a great influence on cognitive psychology, the understanding of how people solve problems, and in the formulation of information-processing models of cognition (Simon, 1996). The classic information-processing model draws parallels between computerised information processing and human thinking and cognition (e.g., Newell & Simon, 1972; Newell et al., 1958; Simon, 1996). According to Simon (1996), the brain converts information to symbols, which are then stored in memory to be retrieved as required. The input information creates symbols and mental representations. In the same manner that a computer manipulates and processes inputs, the brain too manipulates and processes information to generate outputs (Simon, 1996). Thus, human behaviour can be seen as an output of information-processing of mental representations: we see or hear, think, then act. The brain, therefore, is like a complex machine that manipulates inputs to compute solutions.

Newell and Simon (1976) described the brain and computers as physical symbol systems, which possess "the necessary and sufficient condition for a physical system to exhibit general intelligent action" (Newell, 1980, p. 41). Accordingly, problem solving can be explained as a series of mental computations of the input problem information. Newell and Simon's (1972) computational model of problem solving centres on the problem solver's internal representations of the problem space. Fundamentally, the problem space is what the problem solver understands, consisting of an initial state (what she initially sees), the path to solution (her solution attempts) and the goal state (the final solution) (Newell & Simon, 1972). To generate a solution, she creates an internal representation of the problem space and makes solution attempts that will move her closer to the goal. Intelligent information-processing systems, humans and computers, mentally search the task environment in ways to streamline their problem space (Simon & Kaplan, 1989). The ability to search through internal representations is limited by the computational capacity of that intelligent information-processing system. For example, when attempting the Tower of Hanoi problem (see Chapter 2, p. 13), the problem solver creates an internal representation of the entire problem and moves discs in a series of logical steps progressing to the goal. If she develops an appropriate internal representation, the problem space is narrow, and each disc move is planned. The Tower of Hanoi has a clear path to solution and it can always be solved through a series of logical moves (Simon, 1975).

Information-processing is intelligent action performed by the human brain, which can be developed into logical series of algorithms emulated by computers (Newell, 1980; Newell & Simon, 1976; Simon, 1996). In the view that human intelligence could be extended to computers, Newell et al., (1958) developed the *logic theorist* computer program based on observations of human behaviour during problem-solving activity and how people navigated to a solution. The problem-solving processes observed in humans took place by initially breaking down the components of the problem, then creating sub-problems and sub-goals to solve (Newell et al., 1958). Thus, physical symbol systems create symbols of goals, plans and knowledge, which are manipulated mentally. These observations led to the creation of algorithms that could be applied to computers. The logic theorist program learnt to solve a range of problems based on the algorithms. The computer learning provided a foundation for artificial intelligence, in which programs could learn to solve problems through a series of computations (Newell et al., 1958; Simon & Kaplan, 1989). Therefore, computer programs, such as the logic theorist, can generate solutions, and computational models of information-processing can explain solutions, based on the computational capacity of that intelligent information-processing system.

A more recent information-processing approach to human cognition is Baddeley's (2012) multi-component working memory model. According to this model, the mind captures information from its immediate environment and temporarily stores it in one of three memory systems: a visuo-spatial sketchpad, a phonological loop, and an episodic buffer. Visual and spatial information is stored in a visual-spatial sketchpad, and audio information is stored in a phonological loop. The episodic buffer connects long-term memory to the visuo-spatial sketchpad and phonological loop. Information-processing taking place in the episodic buffer focuses attention between the present stimuli in our environment. Controlled by the central executive, the episodic buffer regulates the changing visual-spatial sketchpad and phonological loop in a ‘bottom-up’ information flow, while simultaneously processing information held in long-term memory storage in a ‘top-down’ flow (Baddeley, 2012). Therefore, actions and behaviours are conceptualised as resulting from mental processing taking place in the episodic buffer. The episodic buffer is limited in its storage capacity due to the computational demands (Baddeley, 2000). Nonetheless, it is still considered as an instrument for modelling mental representations of the environment (Baddeley, 2012). Similarly, this conception applies to problem solving: problem information is assumed to be processed and transformed mentally, with executive resources acting as a constraint where lower resources might limit mental processing abilities and performance on insight problems (Chein et al., 2010; Weisberg, 2014). Thus, cognitive results mirror the mental capacity of an individual (Fleck & Weisberg, 2013).

Yet, mental computations and information-processing may only be a part of the answer if we consider the question: “how does cognition happen?”. While there is an understandable role for these theories in explaining human cognition and problem solving, cognition may not be centred on mental and internal representations. Greeno (1989; 1998) attested that cognition explained solely in terms of computations of mental representations was insufficient as it ignores the situated activity of problem solving. Instead, cognition should be understood as an association of individual problem solver and the context she is situated in (Greeno, 1989; see also Lave, 1988). While the Tower of Hanoi task follows a logical sequence and can be easily performed by computer algorithms, most of the everyday problems we encounter are not as well defined and require insight (Kaplan & Simon, 1993). When problem solving in the world, components in the environment offer resources based on the situation and not just mental computations. Thus, cognition should be viewed in relation to the situation rather than internal representations alone (Greeno, 1989).

Research into insight problem solving premise insightful solution come from mental restructuring (e.g., Ohlsson, 2011), often neglecting the environment the problem solver is situated in. This assumption places sole focus on the individual instead of the system configured by the individual, the environment and manipulable objects (Vallée-Tourangeau, 2014). To illustrate, consider the debate within the literature on insight problem questioning whether insight results from conceptually-driven or data-driven restructuring. Fleck and Weisberg (2013) aimed to identify the cognitive processes involved in insight problem solving. Specifically, through verbal protocols requiring participants to narrate their thinking as they worked on problems, they sought to determine whether insight problems were solved through restructuring mental representations. Prior to attempting the problems, participants were provided with training on how to narrate their thinking through two training problems; The Marrying Man and The Matchstick Problems. Then, they attempted The Sock, The Necklace, The Trees, The Triangle of Coins and The Lilies Problems (for a description of these problems, see Table 2.2 in Chapter 2, p. 21). Diverse methods were employed by problem solvers, which were also reflective of the diversity of the five problems and their presentation. The authors concluded that problems were solved through restructuring that was either conceptually-driven or data-driven (Fleck & Weisberg, 2013). Conceptually-driven restructuring recruited mental efforts as the problem solver examining different features of the problem with aim to find something that may cue insight. If restructuring is data-driven, however, the restructuring that takes place during problem solving is “driven primarily by the objects available in the environment” (Fleck & Weisberg, 2013, p. 440) and mental representations were changed in response to a change in the physical configuration of the problem. Data-driven was most pronounced in problems that provided ‘physical props’ for participants to manipulate while problem solving. In other words, restructuring is important for successful insight performance, but the source of restructuring differs. Fleck and Weisberg (2013) note the data-driven restructuring in problems with physical props, such as The Necklace, The Trees and the Triangle of Coins problems, resulted from unintentional explorations of the objects, not a direct consequence of their thinking. Although this is demonstrated, changes in the problem presentation were interpreted as prompting mental restructuring, while the action that changed the problem presentation was ignored.

The contrast in the two forms of restructuring begins to demonstrate the association between thinking, action and perception when problem solvers can reconfigure the problem presentation to facilitate insight (Vallée-Tourangeau, 2014). This can be interpreted as actions and cognitive outputs not exclusively resulting from the mental computations; actions may guide thinking. However, Fleck and Weisberg’s conclusions were indifferent to the central role *interacting* with the physical props had on insight, even though data-driven restructuring was only observed in these problems (Vallée-Tourangeau, 2014). This suggests that information-processing can occur beyond mental representations of what we see, to be guided by the environment and how we act on it to govern cognition (Clark, 2008). As Newell and Simon (1976) themselves state:

> Intelligent action is everywhere around us in the biological world, mostly in human behaviour. It is a form of behaviour we can recognize by its effect whether it is performed by humans or not. The [physical symbol system] hypothesis could indeed be false. Intelligent behaviour is not so easy to produce that any system will exhibit it

willy nilly. Indeed, there are people whose analyses lead them to conclude, either on philosophical or on scientific grounds, that the hypothesis is false. Scientifically, one can attack or defend it only by bringing forth empirical evidence about the natural world. (p. 87 – 88)

Therefore, it could be argued that cognition is not purely a result of mental processing and can be explained beyond classic information-processing models (Gallagher, 2008).

Beyond the Information-Processing Model

Anthropologists, philosophers and, more recently, cognitive psychologists have offered alternative theoretical accounts to explain cognition beyond the information-processing model (Hutchins, 1995; Clark & Chambers, 1998; Vallée-Tourangeau et al., 2015). The most radical approach is to entirely reject the idea of mental representations, in which symbolic processing of mental representations are likened to "mental gymnastics" (Chemero, 2009, p. 43). Such an approach suggests cognition arises from the dynamic integration of bodily activity and the extra-bodily environment without mental representation (Chemero, 2009). Others have argued that a radical embodied view that rejects mental representation entirely is not the best way to consider cognition, as representation does play an important role in sense-making and understanding (Clark, 2010; Menary, 2010).

The role and relevance of mental representations, however, has been questioned. The so called *four E's of cognition* propose the cognitive processes can be embodied, enacted, embedded and extended in the environment through interaction between the organism and the surrounding environment (Clark, 2008; Clark & Chalmers, 1998; Gallagher, 2008; Varela et al., 1991). The point of departure of cognitive processes are not mental representations, but bodily action in the situated environment (Menary, 2015). The body is the point of contact where mind meets behaviour, and our primary contact with the world is an embodied experience of sensorimotor, physical action (Gallagher, 2005; 2008). The way we enact and interact with the environment offers both the opportunity to explore multiple possibilities, while also constraining perception and conscious awareness (Gallagher, 2008). The integration between bodily activity and the extra-bodily environment we are embedded in causally influence each other in a dynamic integrated cognitive system (Menary, 2006; Gallagher, 2008). Enacting in the environment alters perception and enhance sense-making and cognition in humans and most living organisms (Thompson & Stapleton, 2009; Varela et al., 1991).

Extended Mind Thesis

The debate on the role of representations does not lend itself to scrutiny and experimentation of the cognitive processes. Of the four E's, the extended mind thesis is the less radical departure from the traditional information processing model. As such, it is worth exploring in more detail. This view begins to unfold how environmental structures and operations provide a useful "stand-in" during information-processing (Clark, 1989, p. 64). Introduced by Clark and Chalmers (1998), the *extended mind thesis* argues that the body and the environment are active parts of the cognitive process, and the mind is extended into the environment to drive cognition (Clark & Chalmers 1998; Clark 2003, 2008; Menary 2007, 2012; Sutton 2010; Theiner 2011; Rowlands 1999, 2010; Wilson 1995, 2004; Wilson & Clark, 2009).

The extended mind thesis is grounded in "active externalism" (Clark & Chalmers, 1998, p. 8): Thinking is not merely a response to action, nor is action a response to thinking. While 'skin and skull' are rejected as the border of the mind, the extended mind thesis does not accept a complete externalist radical embodied view of cognition. Instead, the environment plays an active role in driving cognition, namely active externalism, where thinking and action are dynamically coupled. In this view, when playing scrabble, for example, the action of rearranging the letter tiles to find words is a part of information-processing activity, not a by-product of thinking. Accordingly, Clark and Chalmers (1998) describe active externalism as:

> A part of the world functions as a process which, were it done in the head, we would have no hesitation in recognizing as part of the cognitive process, then that part of the world is (so we claim) part of the cognitive process. (p. 8)

Much like embodied, enacted and embedded views, cognition is not "brain-bound" and there is no separation between the mind and the world. Cognitive processes are extended among three threads; the brain, the body, and the world (Clark, 2008). The brain, the body, and the world create a coupled system, which actively interact: The body extends thoughts through language and behaviour, and the world enables behaviours and thoughts (Chalmers, 2008). As the mind is extended into the world, the environment is integral to the cognitive process, aiding decision making, reasoning and problem solving (Wilson & Clark, 2009). For example, incorporating bodily actions such as using fingers (the body) as an extension to working memory (the brain) to aid difficult calculations invites action and behaviour into the cognitive process. However, "they will not encompass the more contingent aspects of our external environment, such as a pocket calculator [the world]" (Clark & Chalmers, 1998, p. 40). Thus, the body and the world are a vehicle for information-processing activity (Hurley, 1998).

The extended cognition view offered by Wilson and Clark (2009) accepts some tenants of the information-processing model, but objects and people in the environment, are components of the extended, wider computational organisation, which improve and augment the cognitive process (Wilson & Clark, 2009). Extended cognition is structured in two dimensions; external cognitive systems and internal cognitive resources (Wilson & Clark, 2009). The external cognitive system consists of natural, technological and socio-cultural resources in the world. Natural extended cognitive systems are purposeful natural resources, which are integrated into the cognitive system. Wilson and Clark describe the hermit crab that uses a natural resource, an empty shell, to serve an important function, the crab's protection. Although a non-cognitive example, the hermit crab demonstrates how an inanimate object naturally occurring in the environment becomes a tool that can facilitate a need. Technological, or non-natural resources are created developments that serve a function, such as writing notes, which augment cognition (Clark, 2003). Labelled the 007 principle, natural and technological resources allow us to "know only as much as you need to get the job done" (Clark, 1989, p. 64). Socio-cultural resources are structures or groups that perform a role in cognition often overlooked, a sort of "cognitive oxygen" (Wilson & Clark, 2006, p. 13). For example, mathematical notations when doing complex multiplications makes the equation easier to complete without altering an individual's mathematical ability. Whether resources are natural, technological or social-cultural, the non-neural resources must be reliable and durable, where they are "geared toward a specific purpose" (Wilson & Clark, 2009, p. 64).

Distributed Cognition

In the book *Cognition in the Wild,* the anthropologist Hutchins (1995) conducted an ecological study of USS Palau, a US naval ship. The book captured the various ways crew members handled information-processing activity. The successful navigation of the naval ship was contingent upon interactions among the crew and awareness of the constant changing environment, which alter mental representations. Cognitively demanding tasks, such as attempting to stop the ship before reaching a bridge, were performed through interacting with other crew members, never in isolation. The cognitive processes required for manoeuvring towards a harbour were built upon mental representation of the ship's physical and moving positioning, the varying actions of individuals on-board, and their interactions with each other (Hutchins, 1995). Cognition was not observed as an individual mental process, rather acting on the world and a “social distribution of cognitive labour” (Hutchins, 1995, p. 228). A single crew member was unlikely to stop the ship or navigate it to port: It was the interactions of all the crew members as a coordinated dynamic distributed system (Hutchins, 2001).

The observation and analysis of the crew member’s interactions with each other and their environment demonstrated the importance of a coordinated cognitive process to successfully navigate USS Palau. As a result of a series of wide-ranging studies, such as the seamless operations of airplane cockpits and USS Palau, Hutchins (1995) described cognition as occurring through both internal and external representations. External representations guide internal representations, which can prompt and enhance new thought trajectories (Hutchins, 1995; Hutchins, 2001). The *distributed cognition* conceptual framework explained the co-occurrence of internal and external representations as coordination between the brain and environment, which enables thoughts to be processed more effectively, and the formulation of new ideas to be produced easier (Hollan, Hutchins, & Kirsh, 2000; Kirsh, 2009). The internal representations and external representations work together in three ways, where cognition is either distributed through time in which earlier events alter later events, involved in interaction of materials and environment, or distributed socially between people. While the distributed cognition framework embraces the information-processing model as a way of partially explaining thinking and behaviour, it posits that information-processing is not solely computed by internal, mind manipulations. Instead, the cognitive process is spread across both internal and external representations, as in the navigation of USS Palau (Hutchins, 1995). Thus, distributed cognition dissolves the detachment between the individuals’ mind and the individuals’ environment (Hutchins, 2001), bringing the problem solving and the insight process into a situated context (Perry, 2003).

Where cognition is spread across a distributed network, the environment plays an active role in thinking. Thinkers make sense of thoughts by projecting thoughts onto the world (Kirsh, 2006). Projection is actively anchoring mental representations onto the visible world (Hutchins, 2005; Vallée-Tourangeau et al., 2015). Just as a dancer 'marks', making effortless movements of potential choreography to explore the tempo of a phrase, individuals explore and externalise their thoughts to determine whether an action will complete their task (Kirsh, 2009). Sense-making is developed from a cycle of project-create-project in which mental representations are projected onto the visible environment, and then create their thoughts onto the world (Kirsh, 2006). The change created in the visible environment lead to new projections: Thinking informs action, action informs thinking. Action transforms thinking, such as rearranging scrabble tiles in attempt to find a word, or rotating shapes when playing Tetris (Kirsh, 2013; Vallée-Tourangeau & Vallée-Tourangeau, 2017).

Interactive Thinking and Problem Solving

Informed by distributed cognition frameworks, researchers have tested for the effect of interactivity on cognitive performance, often demonstrating that increasing interactivity can leverage cognitive performance in lexical decision in word production tasks (Vallée-Tourangeau & Wrightman, 2010), visuo-spatial tasks using matchstick algebra problems (Weller, Villejoubert, & Vallée-Tourangeau, 2011), transformational problems such as the river-crossing problem (Cowley & Nash, 2013; Guthrie et al., 2015) and mental arithmetic (Guthrie & Vallée-Tourangeau, 2018; Vallée-Tourangeau, 2013). Increasing interactivity has had demonstrative positive impact on the proportion of successful completions of difficult tasks, and efficiency in the length of time taken to complete less complicated transformational tasks. Table 3.1 displays some of this recent data. When problem solving was attempted in a task ecology where participants had limited opportunity to modify the initial task stimulus but were allowed to sketch notes on paper or an electronic tablet condition, those task ecologies are labelled as *low interactivity*. By contrast, where the task ecology enables problem solvers to physically interact with the initial task information to construct a solution, it is labelled as *high interactivity*.

Table 3.1.

A table displaying the findings reported in interactive problem-solving studies. The data reported as a percentage is the proportion of participants who successfully completed the problem, and the data reported as 'secs' are the average latencies to completion. Note: in the River crossing experiments where participants had more than one attempt, the data reported is only of their initial naïve attempt.

Problem Type	Study	Low Interactivity	High Interactivity
Insight	**Cheap Necklace Problem** (Fioratou & Cowley, 2009)	3%	30%
	Matchstick Algebra, Type A (Weller et al., 2011)	73%	63%
	Matchstick Algebra, Type B (Weller et al., 2011)	36%	57%
	Matchstick Algebra, Type C (Weller et al., 2011)	12%	30%
	Matchstick Algebra, Type D (Weller et al., 2011)	20%	52%
	17 Animal, Experiment 1 (Vallée-Tourangeau et al., 2016)	0%	26%
	17 Animal, Experiment 2 (Vallée-Tourangeau et al., 2016)	17%	54%
Reasoning	**Bayesian Reasoning Problem, Experiment 1** (Vallée-Tourangeau et al., 2015)	52%	73%
	Bayesian Reasoning Problem, Experiment 2 (Vallée-Tourangeau et al., 2015)	9%	57%
	Bayesian Reasoning Problem, Experiment 5 (Vallée-Tourangeau et al., 2015)	52%	77%
Transformational	**River Crossing, Experiment 1A** (Guthrie et al., 2015)	337 secs	426 secs
	River Crossing, Experiment 1B (Guthrie et al., 2015)	463 secs	493 secs
	River Crossing, Experiment 2 (Guthrie et al., 2015)	408 secs	393 secs
	Mental Arithmetic, Without Articulacy Suppression (Vallée-Tourangeau, et al. 2016)	56%	63%
	Mental Arithmetic, Without Articulacy Suppression (Vallée-Tourangeau, et al. 2016)	38 secs	31 secs
	Mental Arithmetic (Guthrie & Vallée-Tourangeau, 2018)	60%	69%
	Mental Arithmetic (Guthrie & Vallée-Tourangeau, 2018)	27 secs	26 secs

In so-called “interactive” environments, thinkers can make arbitrary moves, which may assist in the drastic reshaping of the problem in the physical representation (Kirsh, 2009). This ‘spatial rearrangement’ modifies and restructures the problem, which is the shaping and reshaping of the problem representation (Kirsh, 2010, 2013; Kirsh & Maglio, 1994). The perceptual change may afford cues to new strategies, enabling better planning and efficiency in progressing towards a goal. If a cognitively challenging task in the form of an insight problem is presented and the problem solver is able to restructure the problem, that task is ‘cognitively congenial’ (Kirsh, 1996).

For example, Vallée-Tourangeau et al. (2015) explored the agent-environment ecosystem when altering the level of interactivity provisioned through a series of experiments using difficult statistical reasoning problems. Naïve reasoners were presented with Bayesian reasoning problem data from which they were required to draw statistical inferences. For example, participants were asked:

> The Head Teacher at Teddington School wonders if watching too much TV increases the chances of wearing glasses. He obtained the following information: 12 out of every 20 pupils watch too much TV. Among these 12 pupils who watch too much TV, 6 wear glasses. Among the 8 remaining pupils who do not watch too much TV, 2 also wear glasses. Imagine you meet a group of pupils who wear glasses. How many of them watch too much TV? (p. 585)

In the first of five experiments, participants were asked to answer three similar question and report their answers as natural frequencies, i.e., 3 out of 4 pupils watch too much TV. The problem data was presented either in a paper-and-pencil, low interactivity condition, or a high interactivity condition in which a set of custom-made playing cards representing the problem data was provided in addition to paper-and-pencil. The high interactivity participants were made aware that the cards represented the elements of the problem they were working on and they should arrange them to aid in the difficulty of the task, but they were not shown how to arrange the cards. The participants were randomly allocated into either the low interactivity condition to attempt all three questions, or the high interactivity condition. It was reported that participants in the high interactivity version gave more accurate statistical inferences compared to those in the low interactivity version. This finding was independent of the numeric ability of participants, suggesting that the ability to interact with physical models of problem information successfully improved statistical reasoning. The second experiment in which a new group of naïve reasoners were required to draw statistical inferences from single-event probability statements (i.e., 75% of pupils watch too much TV) further demonstrated that the increased level of interactivity enhances Bayesian reasoning performance. Both these experiments taken together demonstrate when afforded the possibility to manipulate objects in the environment, reasoning skills are enhanced irrespective of numeracy skills or whether the problem information is presented in frequencies or percentages.

Interactivity has also been shown to support insight problem-solving performance, more specifically. For example, Weller et al. (2011) adapted the Matchstick algebra insight problem by Knoblich et al. (1999, for a review see Chapter 2, p. 15) to explore insight when the level of interactivity in this task was increased. The Roman numerals equations were either presented in a “static” or an “interactive” version. In the static version, participants were asked to mentally transform the expressions and to note their answers using paper-and-pencil only. The interactive version provided participants with a magnetic board and magnetised matchsticks. They first had to recreate the false Roman numeral expression and then attempt to make it true. Unremarkably, the easiest Type A problems were solved most frequently, where the static version had a slightly higher mean percentage of correct response. However, in the more difficult Type B to D problems, participants in the interactive task significantly outperformed the static group. Replicating the pattern observed by Knoblich et al. (1999), in the static version of the task, performance varied across version types, where insightful solutions were less frequent the harder the expression types. However, this pattern was not observed in the interactive condition. The number of correct responses for easiest Type A problems did not different significantly from those of the hardest Type D problems when participants could physically transform the expressions. When completing an easier task, such as the Type A matchstick algebra problems, increased levels of interactivity may not be as beneficial as engaging in pure mental processing. However, when the task complexity increases, an increase in the level of interactivity may greatly enhance insight problem solving as participants can engage in physical actions and manipulations. It is worth noting that the original study by Knoblich et al. (1999) presented the Roman expressions in two separate blocks of 6-Matchstick algebra problems each, to examine transfer. The transfer effect in the second block of Knoblich et al. also produced high solution rates for the hardest Type D problems. Transfer, however, was not examined in Weller et al.'s investigation on the role of interactivity on insight. This raises the question as to whether the effect of interactivity is stronger than the transfer effect in promoting insight. This will be discussed in more detail later in the thesis.

Increasing interactivity also allows participants to overcome an impasse in insight problem solving. For example, Vallée-Tourangeau, Steffensen, Vallée-Tourangeau and Sirota (2016b) explored insight performance in the 17A problem. Problem solvers were asked: "How do you put animals in four enclosures in such a manner that there are an odd number of animals in each of the four pens?" (Vallée-Tourangeau et al., 2016b, p. 197). Although this problem initially presents itself as a straightforward arithmetic problem, it is a spatial problem in which the solution requires overlapping the pens. In one condition, participants experienced the problem in a high interactive condition where they could physically create pens using pipe cleaners that varied in length, with 17 zebra models. In the other condition, participants sketched the pens on an electronic tablet using a stylus. All participants were permitted three minutes to sketch an answer on paper, then spent 25 minutes on working memory tests before returning to the 17A problem in either the tablet or interactive condition. None of the participants produced a solution in the initial three-minute period in either condition, all reaching an impasse. In the subsequent attempt, no solutions were produced in the tablet condition. By contrast, the high interactive task environment in the physical model condition significantly improved the likelihood of producing a correct solution, or a partial solution in which they overlapped the pens without distributing the animals correctly. Only those in the high interactive condition were able to overcome the impasse. By creating and recreating physical constructs, which consistently altered the perceptual layout of the visual environment, the inappropriate constraint of it being an arithmetic problem was liberated.

Beyond interactivity, the properties of the artefacts available to represent the task information also helped. Following a similar experimental procedure, Vallée-Tourangeau et al. (2016b, Experiment 2) explored whether it was the materiality of the artefact or the interactive task ecology which enhanced insight performance. Instead of using pipe cleaners, participants were given four metal hoops to represent the pens. Participants in the low interactivity (tablet) condition were still required to sketch a solution using a stylus but they were also shown an image of the four metal hoops and animal figurines prior to their solution attempts. Insightful performance improved in this experiment, as the metal hoops encouraged an overlapping strategy not observed in their first experiment. Still, insightful solutions were reported significantly more frequently when participants were able to construct a physical model of the problem. Even though the materials changed between experiments, the key enabling feature remained the opportunity to physically alter the problem presentation to break the impasse.

It is unclear, however, what role incubation may have played in these different task ecologies. All participants were given three minutes to attempt to solve the problem on paper followed by 25-minutes of working memory test before returning to the problem. It is unclear how this initial period may be implicated in the performance rates reported. As they were presented with the problem information and actively engaged in solution attempts, it is possible that the subsequent 25-minutes acted as an incubation period. While not the intention, nor the motivation of Vallée-Tourangeau et al.'s study, this raises the question of whether the effect of interactivity interacted with the effect of incubation to help participants overcome the impasse. This point is re-raised later in the thesis.

The role of interactivity on insight problem solving was also investigated using the Cheap Necklace Problem (CNP, see Chapter 2, p. 39). Grounded on the premise that cognition occurs in a distributed cognitive system, Fioratou and Cowley (2009, Experiment 1) presented participants the problem with varying interactivity levels. All problem solvers were shown the CNP in its standard form, with a piece of paper detailing the instructions and a schema of the initial state, four three-link chains, and the goal state, a complete 12-link necklace. In the first condition, participants were given a pen with which they could sketch and make notes while they attempted to find a solution. The second group received physical chains representing the initial state, which opened and closed. These participants were invited to interact with the chains as they searched for their solution. While most participants failed to produce a solution in both conditions, there was a significant difference in insightful performance between the two groups. Specifically, participants who were able to interact and manipulate the chains produced the correct solution significantly more often. Thus, insightful solutions are most likely to occur when problems solvers and able to interact with manipulables. None the less, the CNP is a difficult insight problem. Similar to the 17A problem, the problem presents itself as a straight forward arithmetic problem. Even though the high interactive task environment promotes insight, participants are still more likely to fail to find a solution than they are to find one (Fioratou & Cowley, 2009). Thus, interactivity significantly enhances insight, but interactivity alone is not always enough to break the impasse for most.

Systemic Thinking Model of Cognition

The four E's of cognition and the distributed cognition framework do not provide a clear consensus on how the cognitive processes take place, just a "shared enemy" of information-processing of mental representations (Menary, 2010, p. 460). Although they engage and expand the debate of cognition spread across a system, which can include both the mind and the world, they are limited to observations and theoretical debate. The extended mind thesis and the distributed cognition framework forcefully argues that information-processing models are insufficient to encapsulate the fullness of human cognition with accumulating evidence showing that cognitive performance leaps when people are allowed to "think with their hands" in interactive environments, such as the studies presented earlier. However, they do not offer an explicit alternative model to explain *how* cognition may emerge from interactivity if not solely from mental processing. This is not to dismiss or diminish the contribution of these frameworks, but a more detailed processing model of how distributed cognition works and why cognitive performance leaps in interactive environments is needed.

The *systemic thinking model* introduced by Vallée-Tourangeau et al. (2015) and revised in Vallée-Tourangeau and Vallée-Tourangeau (2017) is a first attempt to conceptualise how cognitive events such as insightful solutions may emerge in situations where processing is not restricted to the mental sphere. This model is presented as "a dual-flow systemic model" (Vallée-Tourangeau & Vallée-Tourangeau, 2017, p. 142) in which cognition is a result of either: (i) a deductive processing loop in which cognitive results are informed by mental processes, or (ii) an inductive processing loop, where cognitive results are achieved through unplanned actions and behaviours (see Figure 3.1). In addition, the systemic thinking model introduces a third working memory component, the affordance pool, which is defined as “a short-term storage of action possibilities in working memory” (p. 135). Affordances are non-neural properties of the immediate environment that provide “action possibilities” and constitute our “enactive landscape” (Vallée-Tourangeau et al., 2015; Kirsh, 2009).

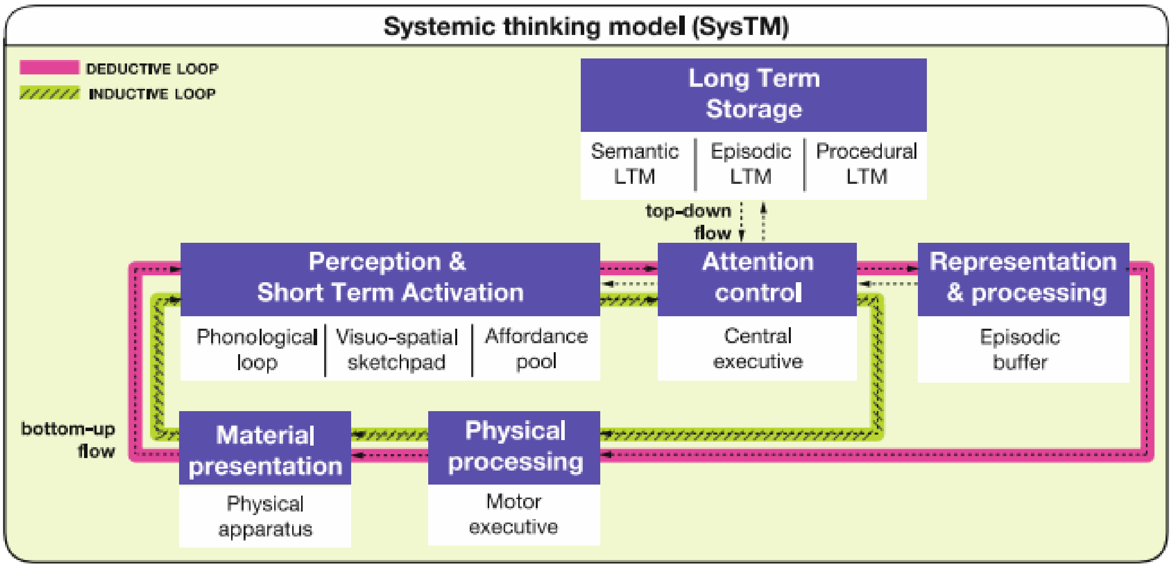

Figure 3.1. The Systemic Thinking Model (SysTM, reproduced from Vallée-Tourangeau & Vallée-Tourangeau, 2017[1])

Similar to Baddeley’s (2012) working memory model, the systemic thinking model assumes that the mind takes information in from its immediate environment. The perception of the stimulus contributes to the formation of a mental representation. As opposed to linear deductions of input-process-output, Vallée-Tourangeau and Vallée-Tourangeau (2017) systemic thinking model proposes information processed in this loop is deduced through both

[1] From Figure 7.2 in Cognition Beyond the Brain: Interactivity and human thinking (p. 142) by Cowley and Vallée-Tourangeau, 2017, London: Springer. Copyright 2017, by Springer Nature. Reprinted with permission.

mental *and* physical processing. In addition to verbal stimuli temporarily activated in the phonological loop and visual cues, in the visuo-spatial sketchpad, motor-action sequences are assumed to be activated in the affordance pool. These latter activations contribute to shaping a mental representation of the stimulus in the episodic buffer, which includes a representation of possible motor actions (Vallée-Tourangeau et al., 2015; Vallée-Tourangeau & Vallée-Tourangeau, 2017). Therefore, actions and behaviours in the deductive processing loop are planned and involve the episodic buffer. We see or hear, think and plan our actions, then we act.

However, in some instances the episodic buffer may not need to be activated to guide behaviour. The material presentation may prompt a direct perception of latent affordances, directly activating stored motor-action sequences which can then be acted upon by the central executive without requiring mental representation and processing. Just as people do not normally stop to decide what they will do next when they face a door in our path (unless it is poorly designed), what we see may prompt action before we have a chance to think (Norman, 2013). In other words, the ability to act directly on material presentations of information allows behaviour and action to be understood not as the result of deductive processing of mental representations, but as inductive processing of physical representations (Vallée-Tourangeau & Vallée-Tourangeau, 2017). Visibility is important for mapping between what you want to do and what appears to be possible. Affordances need be visible and perceivable, not just latent objects in the backdrop (Norman, 2013). In the inductive processing loop, cognitive results develop from a situated agent-environment ecosystem; that is, from an agent situated in, interacting with, and being influenced by her physical environment. The systemic thinking model of cognition proposes that if a problem solver were to be provided with an environment that can be physically manipulated, her perception of affordances or "actions possibilities" can be perceived without the need to be mediated by mental representations

(Vallée-Tourangeau & Vallée-Tourangeau, 2017, p. 145). There is evidence that this is the case for perception tasks. For example, when playing Tetris, Kirsh and Maglio (1994) demonstrated physical rotations of zoid (Tetris shapes) was faster and easier for players than mentally simulating rotations. As such, physical restructuring can be more efficient than mental restructuring alone. While a problem solver is acting upon the perceived affordances, she is also transforming the tasks perceptual input. Changes in the task environment are affordance-driven in which unplanned actions and behaviours yield fruitful precepts without a mental plan (Vallée-Tourangeau et al., 2015; Vallée-Tourangeau & Vallée-Tourangeau, 2017).

Similar to the distributed cognition framework and the extended mind thesis, the systemic thinking model posits that “people and things mutually influence each other” (Vallée-Tourangeau & Vallée-Tourangeau, 2017, p. 140). Uniquely, the systemic thinking model predicts cognitive performance leaps in interactive environments because of *cognitive interactivity*: the “meshed network of reciprocal causations between an agent’s mental processing and the transformative actions she applies to her immediate environment to achieve a cognitive result” (Vallée-Tourangeau & Vallée-Tourangeau, 2017, p. 133). Cognitive interactivity works by putting the emphasis on *affordances*. Actions and interactions influence cognition in the same way that cognition influences behaviour. The distinction between “mind-as-processor vs behaviour-as-reaction” is unnecessary (Vallée-Tourangeau & Vallée-Tourangeau, 2017, p. 140). The affordance pool allows reasoners and problem solvers to engage in both deductive and inductive processing loops, which promotes successful completion of cognitively demanding tasks. Therefore, unguided behaviours and interactions with affordances can augment and support reasoning and problem solving. Behaviours and actions, such as rearranging playing-cards in a more congenial manner, are constitutive of the cognitive process. A change in the task environment and information available can alter how the information is processed without requiring a mental plan. We are active sensors of the world that surrounds us, which inevitably alters our perception and thinking. Information-processing and cognitive activity is more than processing the sense-saturated information: Cognition arises from interacting with the world (Thelen, 2000). In the same manner that a blind man's cane provides an experience otherwise impossible without his tool (Kirsh, 2013), interacting with tools modifies the way we think and perceive.

To summarise, the systemic thinking model highlights the need for studying cognition in an agent-situated environment in which thinkers are free to manipulate and transform their perceptual input. It provides a theoretical framework that characterises the agent-environment ecosystem by the amount and nature of action possibilities or affordances offered by the immediate environment and conceptualise the impact of interactivity on performance through two interdependent "information-processing loops": the deductive loop and the inductive loop. Allowing participants to manipulate physical elements that are representative of the task information offers more opportunities to engage in inductive processing, and more opportunity to stumble across a fruitful percept which may then provide an anchor for more productive deductive processing. In comparison to the limited affordances inherent in a paper-and-pencil set-up may restrict opportunities of insightful thinking and constrains cognitive processing. This explains why increasing the level of interactivity may foster better cognitive results, as long as the problem solver is able to perceive and act upon the affordances in her immediate environment. The methodological implications of adopting a systemic approach to study cognition opens the windows of the psychologist's lab. By inviting scaled down real-world task ecologies, we can explore whether action is premeditated by thinking, or thinking can be guided by unintentional actions.

While the systemic thinking model has yet to be used to inform specific empirical predictions, implicit in its formulation is the assumption that interactivity will enhance cognitive performance through the inductive, unplanned physical processing of the task information. This is corroborated by video-based evidence. For example, Vallée-Tourangeau et al. (2015) observed that participants' in the high interactivity version were actively spending time altering the problem information, arranging and rearranging the cards during their problem solving. While these findings consistently demonstrate that interacting with the physical layout aids cognitive performance, it is not possible to infer whether participants were engaging in a deductive or inductive processing loop. The experimental paradigm of altering the level of interactivity through manipulating what affordances are available to reasoners increases *opportunities* to engage in an inductive processing loop. But only those who effectively act upon those opportunities and actually engage in unguided and unplanned (maybe even random) arrangement of the cards may be prompted to achieve new insights and correct inferences. To test for this possibility, Vallée-Tourangeau et al. (2015, Experiment 4) conducted systematic observations of the actions applied to the information layout in the Bayesian reasoning tasks. To understand how interacting with affordances helps, participants were filmed by a camera recording their hands and the table they were working on. Analysis of the recordings shed light on the qualitative differences in actions relevant to the information processing and representation of the problem. Participants were observed to engage in four types of activity: (i) *Projection*, where no activity with the artefacts (playing cards representing the statistical information in the problem) was observed and participants' thinking appeared to be informed primarily by cognitive processing, (ii) *Marking*, which involved activity that directed attention and perception, such as holding or nudging a card without any changes in the arrangement, (iii) *Presentation change*, where the arrangement and the perceptual layout of the cards was altered, and (iv) *Epistemic activity*, involving actions that supported mental computations, such as counting out the cards. The duration participants engaged in each of these mutually exclusive behaviours, and the proportion of the overall time taken to produce an answer were measured.

The comparative behavioural analysis revealed that successful reasoners were actively engaged in Presentation change behaviour through the reorganisation of the information, moving the cards around and altering the cards arrangements. By contrast, those who drew incorrect statistical inferences spent less time engaged in such actions and instead spent most of their time Marking, making small movements without altering the ways in which the cards arranged on the table. Thus, the presence of affordances alone does not transform cognition, but the way in which reasoners act upon those affordances does.

Furthermore, Vallée-Tourangeau et al. (2015, Experiment 5) established that the improvement in cognitive performance was due to acting upon affordances rather than achieving an adequate final external representation in which reasoners could offload their mental representations: those who were presented with a layout of the cards which they did not construct themselves were less likely to succeed. In other words, participants' multiple actions on the layout and the resulting change in perceptual information were instrumental in fostering the cognitive improvement observed.

Systemic Insight: The interplay between interactivity, incubation and transfer on insight problem solving

In light of the four E's of cognition, the distributed cognition framework, and the systemic thinking model, this thesis sought to further explore insight performance from a systemic thinking perspective. Thinking can be enhanced and transformed, as demonstrated by the experiments that adopt a systemic methodology to manipulate interactivity through affordances (e.g. Fioratou & Cowley, 2009; Vallée-Tourangeau et al., 2015; Vallée-Tourangeau et al., 2016b; Weller et al., 2011). Experimental paradigms that vary in the range of interactions they afford are more representative of thinking and cognition "in the wild".

Neither the representational change theory (RCT) nor the criterion for satisfactory progress theory (CSPT) can adequately explain the cognitive mechanism of insight (see Chu et al., 2007 in Chapter 2, p. 43). Their premise of insight as resulting solely from mental processing overlooks the role of affordances and cognitive interactivity. Classical perspectives on problem solving are embedded in computation models of insight problem solving (Sio & Ormerod, 2009) such as the information-processing model and those presented in Chapter 2. The systemic thinking model perspective offers the opportunity to broaden the debate on insight by exploring how inductive processing and unplanned physical actions contribute in facilitating insight.

This thesis presents *Systemic Insight: The interplay of interactivity, incubation and transfer on insight problem solving*. The subsequent chapters aim to broaden the discussion on insight problem solving by adopting the systemic thinking methodology and bringing "the wild" into the psychologists' lab. Past evidence showed that a dynamic and interactive task environment can promote insightful solutions (Weller et al., 2011; Vallée-Tourangeau et al., 2016b; Fioratou & Cowley, 2009). While participants in Silveira's (1971) experiment did not have access to a physical representation of the problem, they were aided by a prolonged incubation period. Similarly, the experiments by Fioratou (2005) explored the benefit of transfer in a paper-and-pen abstract environment only. Whether and how a more dynamic, interactive version of the problem is implicated in incubation and transfer is yet to be established. Thus, in addition to contributing further evidence to the impact of increased interactivity on insight performance, this thesis sought to contribute to knowledge on systemic cognition by investigating how interactivity may interact with incubation and transfer to promote insight.

Four experiments were conducted using the CNP as a paradigm for these investigations. Two experiments sought to investigate whether incubation interacted with interactivity (Chapter 4), while the other two examined transfer (Chapter 5). Conceptualising problem solving as resulting from action following either a deductive or inductive processing, the work also explores if and how affordances prompt insight in a dynamic agent-environment by recording and analysing participants' actions (Chapter 6). In line with systemic thinking model terminology, the subsequent chapters distinguish the different interactivity levels afforded to participants as either *low interactivity*, such as a paper-and-pen "abstract" version writing does, to a lesser degree, facilitate in cognition, or *high interactivity*, where participants are able to physically manipulate the task environment.

Chapter 4: Interactivity and Incubation

Initial efforts to solve insight problems usually fail. The most obvious solution rarely produces the desired goal. Typically, problem solvers spend some time attempting their strategy before getting stuck. Leaving the problem aside for some time often helps break an impasse. As we have already reviewed in Chapter 2 (p. 31), an incubation period, where a problem solver is not consciously engaged in the task, often leads to more creative solutions (Gilhooly et al., 2010). The incubation period may help restructure mental representations into a more productive, more adequate use of problem information (MacGregor et al., 2001). Withdrawing attention from a problem that resists a solution can promote insight solutions when reattempted (Segal, 2004; Sio & Ormerod, 2009).

The 17A insight problem, which asked problem solvers to place 17 animals into four enclosures with an odd number of animals each was investigated by Vallée-Tourangeau et al. (2016b, see Chapter 3, p. 67). Participants attempted the problem using either an electronic tablet to sketch their solution, or pipe cleaners and 17 animal figurines to create their solution. All participants were permitted an initial preparation period in which they could sketch thoughts and ideas on a piece of paper, and even note a solution if they could find one. This initial period, albeit just three minutes, gave their participants time to familiarise themselves with the problem. More crucially, participants were able to realise that the problem was not a simple arithmetic one. Although a longer preparation period than three minutes is better for incubation (Silveira, 1971, Experiment 1), all participants reached an impasse in both conditions and both experiments. A prolonged incubation period vastly promotes insight, especially when the interruption took place after participants engaged with the problem for a longer period of time (Silveira, 1971). Thus, the 25-minute period working on unrelated working memory tests may have served as a filled incubation period in which new solutions began to emerge. The 17A study makes no mention of incubation, or its potential implication on insightful performance. This is not surprising as none of the participants in the tablet condition were able to find a solution to the problem, thus there were no incubation effects to mention (Experiment 1). In the second experiment, where more amenable metal hoops were used to represent enclosures and the tablet condition were shown an image of them, insightful performance increased in both the versions following the working memory tests.

Incubation effects may be facilitated by the problem presentation. Incorrect representations fade during the incubation period, which is a key tenent to achieving insight (Segal, 2004). An incubation effect may not be explanatory for subsequent insight in either of the 17A experiments, but the findings reported by Vallée-Tourangeau et al. raise an interesting question: Whether the effect of a high interactive task environment is in any way affected by incubation. Or rather, whether an incubation effect is affected by the level of interactivity afforded. The ability to extend mental representations through cognitive interactivity may further enhance insightful attainment beyond the incubation period. A richer, more dynamic representation of a problem may facilitate new strategies and relax these inappropriately held constraints (MacGregor et al., 2001). In turn, a break in active engagement may allow for randomness and chance in insight attainment, which serve to augment thinking and inspire new creative approaches with the help of affordances (Kirsh, 2014).

The experiments in this chapter investigated whether an incubation effect is impacted by the level of interactivity afforded. Investigations into the Cheap Necklace Problem (CNP) have demonstrated that insightful solutions are facilitated by incubation (Silveira, 1971) and through interactivity with affordance (Fioratou & Cowley, 2009). Thus, the CNP was used to explore incubation, interactivity and insight. The experiments presented in this chapter have been peer-reviewed and published by Henok, Vallée-Tourangeau and Vallée-Tourangeau (2018).

Experiment 1

The aim of Experiment 1 was to examine whether the level of interactivity afforded would alter incubation in the CNP. Adopting a systemic methodology, participants worked on the problem in either a low interactivity version or a high interactivity version. Based on previous literature, insightful solutions were expected to be influenced by the level of interactivity afforded by the task environment (Vallée-Tourangeau & Vallée-Tourangeau, 2017). Manipulating the physical elements of the problem yields a higher solution rate than simulating moves mentally. Specifically, those in the high interactivity condition would produce insightful solutions more frequently than those in the low interactivity environment (Fioratou, & Cowley, 2009; Weller et al., 2011; Vallée-Tourangeau, 2013).

To examine whether an incubation effect was moderated by the level of interactivity, participants returned to the problem after a two-week delay. Based on the incubation literature, insightful solutions are expected to be found most frequently after an incubation period. Operationalising incubation under laboratory conditions often proceeds with an interpolated period that encourages reasoners to abandon working on the primary task for a short period of time, usually a few minutes (e.g., Patrick, 1986; Segal, 2004; Gilhooly et al., 2009; Silveira, 1971). However, it is sometimes difficult to determine the exact length of the incubation period (Sio & Ormerod, 2009). Anecdotally, in sciences and arts, examples of incubation span over much longer period of time, weeks or months (Weisberg, 2014). Although it is more difficult to control activities participants engaged with during the longer span, it offers incubation as manifested outside the psychologist’s laboratory. Thus, incubation in this Experiment is explored spanned over weeks, rather than minutes.

The solution latencies, how quickly participants arrive at the correct solution, was also measured. This was to explore how altering the level of interactivity may affect solution latencies. It was expected that those who solved the problem upon their initial encounter (Time 1), should solve the problem again and faster after the incubation period (Time 2). In addition, participants' memory ability as a potential moderator of insight performance was profiled. As there is increasing evidence to suggest that working memory is implicated in insight problem solving (e.g., Chudersky, 2014), individual differences in working memory span were also investigated. However, tests and measures of working memory and problem-solving performance that inform the correlational analyses usually proceed in task environments that afford little or no interactivity. Thus, this experiment aimed to determine the extent to which working memory capacity would predict performance. Completing a difficult task has shown to temporarily undermine subsequent efforts that requiring executive controls, such as working memory (Schmeichel, 2007), while interactivity reduces the demand on the available cognitive resources (Vallée-Tourangeau, Sirota, & Vallée-Tourangeau, 2016). Improved performance in interactive tasks is in part explained by offloading working memory. As such, Experiment 1 sought to determine whether interactivity will have an effect on working memory performance by measuring working memory for both low and high interactivity participants, using a computation span task (Ashcraft & Kirk, 2001).

A long-term memory task was developed based on the material reported in Roediger and Karpicke (2006); participants were presented with a short description of the Sun (qua celestial body) and were tested for their memory of that material at Time 1 and again at Time 2, computing a difference score to determine the rate of memory decrement. This was used to determine whether participants with better long-term memory would perform better at Time 2. Although this was an exploratory measure and a specific prediction could not be made, it is possible that better long-term memory made it easier for participants to remember the strategies they employed at Time 1, not their usefulness. Alternatively, better long-term memory may have helped participants dismiss unsuccessful strategies quicker, creating a more efficient problem space.

Method

Participants. An a priori goodness-of-fit analysis based on a GPower analysis of Fioratou and Cowley's (2009) effect size determined the total sample size required was a minimum of 55 participants in each of the following experiments to have 80% power for detecting a medium sized effect when employing the traditional .05 criterion of statistical significance. In the present experiment, 74 participants from Kingston University volunteered to participate in exchange for research participants' credits. However, 11 participants did not return for Time 2, thus were excluded from analysis. Of the remaining 63 participants, 53 were females and had a mean age of $M_{\text{age}} = 22.05$, $SD = 4.05$. All participants were naïve to the Cheap Necklace Problem (CNP) prior to participation.

Materials. A six-page problem pack was given to participants at both Times 1 and 2. The packs included an informed consent form, a video release form when participants were recorded, a short informative article about the Sun (only given at Time 1), the CNP with instructions for those in the low interactivity condition or with a set of four metal chains consisting of three-links for those in the high interactivity condition, as in Figure 4.1. Low interactivity participants were presented with the task on a sheet of paper, with the problem written at the top and lined space to write a solution. The high interactivity participants were given four metal chains consisting of three oval-shaped links, which could be opened and closed by screwing the top of each link.

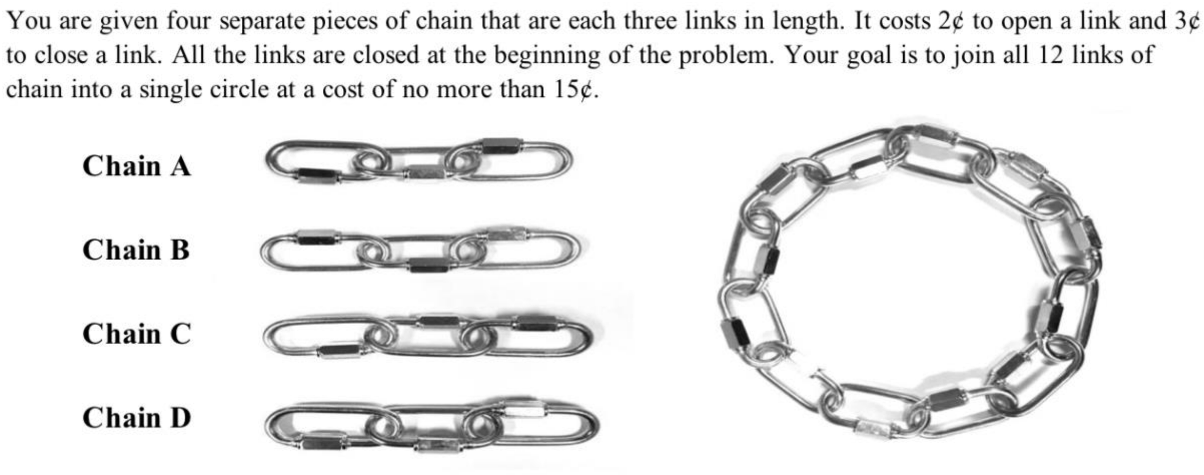

Figure 4.1. The Cheap Necklace Problem as presented to participants in this thesis.

Design and Procedure. This experiment employed a 2 × 2 mixed design, where the between-subject factor was level of interactivity (low interactivity vs. high interactivity) and time as a within-subject factor (Time 1 vs. Time 2). At Time 1 participants initially attempted to solve the Cheap Necklace Problem in either a low interactivity or high interactivity, repeating in the same condition at Time 2 two weeks later. All testing was conducted individually in a quiet observation lab room.

Time 1. Participants were given 5 minutes to read a short summary about the Sun that contained 30 separate ideas written in 256 words (adapted from Roediger & Karpicke, 2006). They were then presented with the CNP and the instructions were read aloud by the researcher. In the high interactivity condition, participants were shown how to open and close links. Participants had up to 30 minutes to complete the task, with the option to stop whenever they chose. When participants announced they were ready to start the problem, the exact time they began could be recorded. Once they were ready to announce their answer to the problem, participants were asked to write it down and explicitly state when they completed so the total time to completion could be noted. Participants were then given a recall sheet, where they were asked to note in either full sentences or bullet-points any information they could remember from the short informative article they read before attempting the CNP; memory was tested after participants had attempted the CNP, which was up to 30 minutes after initially reading the article. They were given 5 minutes to note their response. Participants were then debriefed, but no feedback on performance was given. At this time, they were asked to return to the lab two weeks later, and not to discuss or work on the CNP during that period.

Time 2. Two weeks later participants were given 5 minutes to note anything they could remember from the short description of the Sun presented at Time 1. Long-term memory performance was indexed by taking the difference in the number of distinct ideas recalled at Time 1 and Time 2: The greater the difference in recall, the sharper the decline in memory performance at Time 2. They were then presented with the CNP and instructions were read aloud. Participants in the high interactivity condition were shown how to open and close the links. Once participants indicated they were ready to begin the problem, they had up to 30 minutes to complete the task. Once they noted their solution and stated they completed the CNP, the time taken to complete the task was noted. A computation span working memory task was then presented to the participants. The C-Span working memory task (adapted from Ashcraft & Kirk, 2001) asked participants to read simple arithmetic expressions and announce their answer. Later, they were asked to remember the second number for each expression presented. Participants were instructed to provide a correct answer to the arithmetic task, with accurate recall only being recorded if they had given the correct answer. Participants started by answering one expression, only being required to recall one number. These expressions then increased incrementally up to seven arithmetic expressions in a row, until they had completed 56 arithmetic expressions. To ensure homogeneity in presentation, they were shown the C-Span task in a video, with 4-seconds per question to respond. Scoring was based exclusively on accurate recall.

Results

Correct solutions to the Cheap Necklace Problem were measured in both frequency of successful completion, and the combined effect of interactivity and incubation. Latencies to solution, the time it took participants to reach a solution, was used as a measure of the impact of incubation on the Cheap Necklace Problem. Long-term memory was measured to determine if improvements in performance through time were explained by better long-term memory. In addition, computation span working memory test was used as a means of assessing whether enhanced performance through increased interactions was attributed to improved distribution of internal cognitive resources.

Cheap Necklace Problem Performance

Solution Rates. Successful performance was classified using Silveira's (1971) solution of deconstructing one chain into three-links at a cost of 6¢ and using those three-separate links to combine the remaining three chains into a single circle at a cost of 9¢. Solution rates are reported in Table 4.1: Twelve (or 43%) of the participants solved the problem in the high interactivity condition at Time 1, while 2 (or 6%) solved the problem in the low interactivity condition; the different in solution rates was significant, $\chi^2(1, N = 63) = 12.42, p < .001$. At Time 2, all the participants who solved the problem at Time 1, in both interactivity conditions, offered a correct solution. Of the 16 participants who had not solved the problem in the high interactivity condition at Time 1, 7 (or 43%) solved it at Time 2; of the 33 participants who were unable to solve the problem in the low interactivity condition at Time 1, 5 (or 15%) solved it at Time 2; the difference was significant, $\chi^2(1, N = 49) = 4.77, p = .029$. Because one of the four cells of the contingency table had an expected frequency lower than five, a Fishers exact test was also conducted. This was significant, $p = .040$, supporting the initial Chi square test.

Table 4.1.

Solution frequencies in the low and high interactivity conditions at Time 1 and 2, along with solution latencies.

	Low Interactivity				**High Interactivity**			
Time 1	Yes		No		Yes		No	
Freq	2		33		12		16	
%	6%		94%		43%		57%	
Latency to Solution								
M	806.5				787.3			
SD	333.0				247.0			
Time 2	Yes	No	Yes	No	Yes	No	Yes	No
Freq	2	0	5	28	12	0	7	9
%	100%	0%	15%	85%	100%	0%	44%	56%
Latency to Solution								
M	227.5		371.4		315.3		496.9	
SD	108.2		227.5		155.0		218.9	

Performance Analysis. To further explore the effects of interactivity and transfer, and their potential interaction, an additional performance analysis was completed. A 2 × 2 Mixed ANOVA tested for the between-subject effect of level of interactivity (low interactivity, high interactivity), and the difference in performance between Time 1 and Time 2 as the within-subject factor with CNP performance scored as 0 = never solved, 0.5 = solved once, 1 = solved twice. At both Time 1 and Time 2, the high level of interactivity offered by interacting with the chains significantly increased overall performance: $M_{\text{high}} = .55$, $SD = .44$, $M_{\text{low}} = .13$, $SD = .28$, $F(1, 61) = 21.86$, $p < .001$. Participants were also significantly more likely to achieve insight following an incubation period: $M_{\text{Time1}} = .22$, $SD = .42$, $M_{\text{Time2}} = .41$, $SD = .50$, $b = .76$, $F(1, 61) = 15.36$, $p < .001$. However, the effect of incubation did not vary as a function of the level of interactivity, $F(1, 61) = 1.14$, $p = .289$.

Latencies. For participants who solved the problem both times, latencies to solution, measured in seconds, were considerably lower at Time 2 compared to Time 1: $M_{\text{Time1}} =$ 790.01 sec., $SD = 245.37$, $M_{\text{Time2}} = 302.71$ sec., $SD = 149.11$. A 2 × 2 Mixed ANOVA on latencies to successful solution, using level of interactivity (high interactivity, low interactivity) as the between-subject factor and time (Time 1, Time 2) as the within-subject factor in which CNP performance was scored as 0 = never solved, 0.5 = solved once, 1 = solved twice, showed a main effect of Time, $F(1, 12) = 26.8$, $p < .001$, but the main effect of level of interactivity, $F(1, 12) = .076$, $p = .787$, and the interaction between time and interactivity, $F(1, 12) = .277$, $p = .608$, did not significantly differ. Thus, latencies to solution were quicker at Time 2 as an effect of incubation, not the level of interactivity.

Several unsuccessful participants gave up prior to the 30 minutes permitted. To explore whether diligence on the task altered between interactivity conditions or if those who were more diligent were more likely to find the solution following an incubation period, how quickly participants gave up was assessed. There is no theoretically driven hypothesis for this analysis, as such, is exploratory. Of the unsuccessful participants in the low interactivity condition, seven participants persevered for 30 minutes. In the high interactivity condition, among the 16 unsuccessful participants, 3 worked on the problem for 30 minutes. However, a better measure of diligence might be offered by the time spent on the problem by those who gave up before the allocated 30 minutes. Participants who gave up working on the problem did so quicker in the low interactivity (M = 521s, SD = 472) than in the high interactivity (M = 764s, SD = 447) condition, a marginally significant difference, $t(37) = - 1.99$, p =.054. This in turn suggests that time working on the problem for the unsuccessful participants at Time 1 could predict success at Time 2, independent of the level of interactivity. And while participants who first solved the problem at Time 2, spent on average 4 additional minutes working on the problem during Time 1 (M = 1029.0, SD = 632.8) compared to those who did not solve the problem at Time 2 (M = 787.5, SD = 571.1) this difference was not significant, $t(47) = 1.24$, $p = .221$.

Memory Performance

Both long-term memory and working memory were measured. First, long-term memory scores from the sun extract recall (SER) task (Roediger & Karpicke, 2006) was used to determine if improved performance over time was a function of better long-term memory. Second, in order to examine whether individual differences in cognitive resources may explain differences in performance in the high interactivity condition, working memory was assessed comparing those who did and did not solve the problem, which was observed in both interactivity conditions. Thirdly, to determine whether initial efforts on the CNP would deplete the working memory resources, a comparison between interactivity conditions performance in the C-Span test was undertaken.

Long-term Memory. Memory decline was measured as the difference in the number of separate ideas expressed in the Sun vignette, recalled at Time 2 and Time 1 respectively. Decline was consistent across participants in both conditions, M_{high} = -3.71, SD = 1.94, M_{low} = -3.23, SD = 2.07. It was also consistent as a function of performance, $M_{\text{successful}}$ = -3.64, SD = 1.98, $M_{\text{unsuccessful}}$ = -3.32, SD = 2.05. A 2(successful, unsuccessful) × 2 (low interactivity, high interactivity) between subjects ANOVA confirmed those impressions: the main effect of having solved the problem, $F(1, 59) = .080$, $p = .778$, and level of interactivity, $F(1, 59) = .216$, $p = .644$, were not significant, nor was the interaction, $F(1, 59) = 1.54$, $p = .220$. In other words, long-term memory did not account for improvements in performance across time.

Working Memory. Working memory capacity was measured by assessing performance on a computation span (C-Span) test at Time 2. Participants who successful solved the CNP at least once generally had higher C-Span scores than those who did not solve the problem, $M_{\text{successful}}$ = 22.12, SD = 10.27, $M_{\text{unsuccessful}}$ = 12.97, SD = 8.45. This was observed in both interactivity conditions, M_{high} = 20.67, SD = 10.31, M_{low} =13.34, SD = 8.96.

Two separate analyses were conducted to explore whether working memory significantly moderated CNP performance. Firstly, a 2 (successful, unsuccessful) × 2 (low interactivity, high interactivity) between subject ANOVA measured the combined effect of interactivity and working as independent variables on the CNP performance as a continuous dependent variable (0 = never solved, 0.5 = solved once, 1= solved twice). Those who solved the problem scored significantly higher on the C-Span than those who did not, $F(1, 59) = 6.84$, $p = .011$, but working memory capacity did not differ between participants in the high interactivity condition and low interactivity condition, $F(1, 59) = 1.64$, $p = .206$. The interaction was also not significant, $F(1, 59) = .039$, $p = .844$.

Secondly, to explore whether low interactivity burdened working memory, C-Span performance after attempting the CNP was compared between interactive conditions. An independent sample t-test measured the effect of interactivity as an independent variable on working memory score as the dependent variable. Those who completed the CNP in a high interactive condition performed significantly better in the subsequent C-Span working memory measure compared to those in the low interactivity condition, $M_{high} = 20.7$, $SD = 10.3$, $M_{low} = 13.3$, $SD = 8.9$, $t(61) = 3.02$, $p = .004$.

Discussion

This first experiment examined the role of interactivity on the CNP in addition to the impact of a two-week incubation period on performance. Performance was significantly better when participants were given metal chains in the high interactivity condition compared to when they were restricted to using paper-and-pencil in the low interactivity condition. Further, more participants completed the problem at Time 2, and those participants who completed the task successfully on both attempts were quicker in finding a solution upon their second encounter with the problem. More importantly, participants who did not solve the problem at Time 1 were more likely to solve the problem at Time 2 in the high interactivity condition. Thus, the incubation effect was largest in the high interactivity condition. Performance at Time 2 could not be explained in terms of better long-term memory, although higher working memory capacity was associated with better performance in both the high and low interactivity conditions. Working memory, however, may be implicated in explaining the positive impact of interactivity. Participants in the low interactivity condition had lower scores on the final C-Span test, compared to participants in the high interactivity condition. One possibility would be that even though they were randomly allocated, participants in the low interactivity condition had, on average, a lower working memory capacity. An alternative possibility, however, is that participating in the low interactivity condition resulted in depleted working memory resources and caused the lower C-Span results. This is consistent with recent findings showing that depleting executive control resources impacts performances in low interactivity conditions but not in higher interactivity conditions (Vallée-Tourangeau et al., 2016a).

The CNP is a difficult problem, and the solution rates observed in Experiment 1 are consistent with those reported previously (e.g., Fioratou & Cowley, 2009; Fioratou et al., 2010; Silveira, 1971). When initially presented with the problem in the low interactivity condition, just two participants were able to find the solution. This low solution rate is in part explained by how quickly participants gave up. Fewer participants in the low interactivity condition persevered for the entire 30-minutes allotted, compared to those in the high interactivity. A measure of diligence, assessing those who gave up before the allocated time, indicated participants were less diligent in the low interactivity condition. Diligence predicted performance in Time 2, where regardless of interactivity condition, spending less time working on the problem at Time 1 undermined Time 2 performance. In other words, being less persistent in attempting to solve the CNP in the first session was detrimental to the incubation effect.

The two-week incubation period may have helped participants relax their self-imposed, inappropriate constraints of focusing on the four chains, not the three-links that create the chain (MacGregor et al., 2001). The break in engagement between initially attempting the CNP and reattempting was beneficial to participants, in line with findings from Silveira (1971). While these results are in line with research exploring incubation and investigations on the benefit interactivity, this first experiment suggest that the incubation effect does not vary as a function of the level of interactivity. A second experiment was designed to further assess the role interactivity plays in incubation.

Experiment 2

The level of interactivity present in the problem presentation significantly impacts people's ability to gain insight, both before and after an incubation period. The higher level of interactivity provided a richer, more dynamic representation of the CNP, where interactions allowed for greater opportunities and possible paths to solution. This raises the question whether the larger increase in solutions rates at Time 2 in the high interactivity version is driven by restructuring through incubation on a richer, more dynamic representation of the CNP (an incubation-driven performance improvement) or by restructuring through enactment on the metal chains at Time 2 (an enactment-driven performance improvement). If performance improvement is incubation-driven, performance in a paper-and-pencil version at Time 2 following a high interactive version at Time 1 after an incubation period ought to remain high. By contrast, experiencing the low interactivity version at Time 1, which is less amenable to restructuring, may offer a limited opportunity for performance to improve at Time 2. Alternately, if performance improvement is enactment-driven, working in a low interactive task environment at Time 1 would impede subsequent performance improvement, even when working in the richer, more dynamic representation of the CNP at Time 2. By contrast, experiencing the high interactive task environment first should afford the possibility for vast improvements in performance at Time 2. These predictions are summarised in table 4.2.

Table 4.2.

Incubation-driven vs. Enactment-driven expected performance rise at Time 2. Time 1 = Initial Interactivity level, Time 2 = Final Interactivity level.

[1]*Denotes small (+) or large (++) increase in performance observed in Experiment 1.*

[2]*Denotes small (+) or large (++) increase in performance expected in Experiment 2, under the (a) incubation-driven or the (b) enactment-driven hypothesis, respectively.*

a) Incubation-driven performance improvement at Time 2

	Final interactivity level	
Initial interactivity level	low	high
low	+[1]	+[2a]
high	++[2a]	++[1]

b) Enactment-driven performance improvement at Time 2

	Final interactivity level	
Initial interactivity level	low	high
low	+[1]	++[2b]
high	+[2b]	++[1]

Method

Participants. Sixty-one participants from Kingston University volunteered to participate in exchange for research participation credits. Of the 61 participants, 56 were female, M_{age} = 21.43, *SD* = 4.21. All participants were naïve to the Cheap Necklace Problem prior to participation.

Materials. As in Experiment 1, participants were given a six-page problem pack at both Times 1 and 2. The packs included the same materials as in Experiment 1, namely informed consent, a video release form for participants who were recorded, the long term memory material (article about the Sun, only given at Time 1), the CNP with instructions for those in the low interactivity condition or with a set of four metal chains consisting of three-links for those in the high interactivity condition. Low interactivity participants were presented with the task on a sheet of paper, with the problem written at the top and lined space to write a solution. The high interactivity participants were given four metal chains consisting of three oval-shaped links, which could be opened and closed by screwing the top of each link.

Design and Procedure. This experiment employed a 2 × 2 mixed design, with a within-subject factor of Interactivity (high interactivity, low interactivity), and the trend of interactivity levels experiences as the between subject factor (low to high interactivity, high to low interactivity). Thus, a similar procedure as Experiment 1 was employed aside from one key change: the problem presentation changed for participants at Time 2.

Time 1. Participants were first asked to read a short summary about the Sun (long-term memory), followed by the Cheap Necklace Problem. The instructions were read aloud by the researcher, and participants in the high interactivity condition were shown how to open and close links. Participants were given 30 minutes to complete the task, and when they'd finished, asked to write down their solution. Their long-term memory was then assessed, debriefed, and given.

Time 2. Two weeks later participants were given 5 minutes to note anything they could remember from the short description of the Sun presented at Time 1. Long-term memory performance was indexed by taking the difference in the number of distinct ideas recalled at Time 1 and Time 2: The greater the difference in recall, the sharper the decline in memory performance at Time 2. They were then presented with the CNP and instructions were read aloud. Participants in the high interactivity condition were shown how to open and close the links. Once participants indicated they were ready to begin the problem, they had up to 30 minutes to complete the task. Once they noted their solution, the time taken to complete the task was noted. A computation span working memory task was then presented to the participants. The C-Span working memory task (adapted from Ashcraft & Kirk, 2001) asked participants to read simple arithmetic expressions and announce their answer. Later, they were asked to remember the second number for each expression presented. Participants were instructed to provide a correct answer to the arithmetic task, with accurate recall only being recorded if they had given the correct answer. Participants starting by answering one expression, only being required to recall one number. These expressions then increased incrementally up to seven arithmetic expressions in a row, until they had completed 56 arithmetic expressions. To ensure homogeneity in presentation, they were shown the C-Span task in a video, with 4-seconds per question to respond. Scoring was based exclusively on accurate recall.

Results

Cheap Necklace Problem Performance

Solution Rates. Successful performance was classified using Silveira's (1971) solution criterion. Solution rates are reported in Table 4.3: Fourteen (or 41%) of the participants solved the problem in the high interactivity condition at Time 1, while 4 (or 15%) solved the problem in the low interactivity condition; the difference in solution rates was significant, $\chi^2(1, N = 55) = 5.03$, $p = .025$; this pattern of solution rates replicates the pattern observed at Time 1 in Experiment 1. At Time 2, all 14 participants who solved the problem in the high interactivity condition at Time 1 solved the problem in the low interactivity condition. Of the 20 who had not solved it at Time 1, 1 (or 5%) successfully did so in the low interactivity condition at Time 2. All four participants who solved the problem in the low interactivity at Time 1, solved it in the high interactivity condition at Time 2; of the 23 who did not solve the problem in the low interactivity condition at Time 1, 14 (or 61%) now solved the problem when they switched to the high interactivity condition at Time 2. Comparing the solution rates at Time 2, while fewer people solved the problem in the low interactivity condition (15, or 44%) than in the high interactivity condition (18 or 67%) the difference was not significant, $\chi^2(1, N = 61) = 3.08$, $p = .079$.

Table 4.3.

Solution frequencies in the low and high interactivity conditions at Time 1 and 2, along with solution latencies.

	Low Interactivity				**High Interactivity**			
Time 1	Yes		No		Yes		No	
Freq	4		23		14		20	
%	15%		85%		41%		57%	
Latency to Solution								
M	755.5				1107.6			
SD	306.6				408.6			
Time 2	**High Interactivity**				**Low Interactivity**			
	Yes	No	Yes	No	Yes	No	Yes	No
Freq	4	0	14	9	14	0	1	19
%	100%	0%	61%	39%	100%	0%	5%	95%
Latency to Solution								
M	278.8		810.2		196.9		1094.0	
SD	148.1		326.1		153.6			

Performance Analysis. To further explore the effects of level of interactivity and order on incubation, a 2- between (increasing interactivity trend, decreasing interactivity trend) × 2- within (Time 1, Time 2) Mixed ANOVA was conducted with CNP performance scored as 0 = never solved, 0.5 = solved once, 1 = solved twice. Considering performance at Time 1 only, participants were more likely to achieve insight in higher interactive task environment: $M_{\text{high}} = .41$, $SD = .50$, $M_{\text{low}} = .15$, $SD = .36$, $F(1, 61) = 5.30$, $p = .025$. At both Time 1 and Time 2, although participants were more likely to gain insight in the high interactivity level, this difference was not significant: $M_{\text{high}} = .56$, $SD = .50$, $M_{\text{low}} = .33$, $SD = .47$, $F(1, 59) = .029$, $p = .865$. Insight was more likely to be achieved following an incubation period: $M_{\text{Time1}} = .31$, $SD = .47$, $M_{\text{Time2}} = .57$, $SD = .50$, $F(1, 59) = 34.57$, $p < .001$. The incubation effect varied as function of the trend of the level of interactivity participants experienced, $F(1, 59) = 27.55$, $p < .001$.The improvement in performance after the incubation period was explained by the trend in interactivity levels experienced. Specifically, when interactivity increased (from low interactivity to high interactivity), participants had the highest rate of improvements. Conversely, when interactivity levels decreased (from high interactivity to low interactivity), there was no incubation effect observed.

Latencies. Latency to solution were lower at Time 2 compared to Time 1 for those participants who had solved the problem both times (see Table 4.3). In a 2 (increased interactivity trend, decreased interactivity trend) × 2 (Time 1, Time 2) Mixed ANOVA in which CNP performance was scored as 0 = never solved, 0.5 = solved once, 1 = solved twice, the main effect of Time was significant, $M_{\text{Time1}} = 1029.39$ sec, $SD = 408.59$, $M_{\text{Time2}} = 215.06$ sec, $SD = 152.13$, $F(1, 16) = 38.7$, $p < .001$, but neither the main effect of trend in interactivity level, $F(1, 16) = 1.15$, $p = .300$, nor the interaction, $F(1, 16) = 3.78$, $p = .07$, were significant. In other words, latencies to solution improved through time as an effect of incubation, not the trend of interactivity level experienced.

Looking at how quickly participants solved the problem at Time 2, for those who had not solved the problem at Time 1, the analysis could only be conducted for participants in the low to high interactivity condition, since only one participant in the high to low condition solved the problem at Time 2. In the low to high condition, Time 2 successful participants were not faster than those who had solved the problem at Time 1, $t(16) = -.299$, $p = .769$. There was no difference in level of perseverance among participants who did not solve the problem at Time 1 in the high interactivity condition ($M = 693$ seconds, $SD = 464$) and in the low interactivity ($M = 716$ seconds, $SD = 386$) condition, $t(33) = .16$, $p = .875$.

Memory Performance

Long-term Memory. Participants' long-term memory was indexed based on the difference in their ability to recall the information they read in the article about the sun at Time 1 and 2. Pooling the data across interactivity conditions, memory decline was a little less steep among participants who solved the problem than among those who did not solve the problem, $M_{successful}$ = -3.45, SD = 1.76, $M_{unsuccessful}$ = -4.85, SD = 2.85. In a 2 (successful, unsuccessful) × 2 (increasing interactivity trend, decreasing interactivity trend) between subject ANOVA, there was a borderline main effect of having solved the CNP, $F(1, 57)$ = 3.95, p = .052. The long-term memory scores did not differ between the trend of interactivity level experienced, $F(1, 57)$ = .229, p = .634; the interaction between performance and trend was not significant, $F(1, 57)$ = .003, p = .955.

Working Memory. Working memory capacity as gauged by performance on a computation span test was measured at Time 2. Across both conditions, participants who solved the CNP at least once generally had higher C-Span scores than those who did not solve the problem, $M_{successful}$ = 22.52, SD = 9.21, $M_{unsuccessful}$ = 18.85, SD = 24.94. However, in a 2 (successful, unsuccessful) × 2(low to high interactivity, high to low interactivity) between subjects ANOVA, the main effect of solving the problem was not significant, $F(1, 57)$ = .230, p = .634, nor was the main effect of trend of interactivity level experienced, $F(1, 57)$ = 1.69, p = .199; the interaction was also not significant, $F(1, 57)$ = .012, p = .914.

In order to determine whether interactivity had an effect on mitigating working memory, C-Span performance after attempting the CNP was compared between interactive conditions. In an independent sample t-test, those who completed the CNP in a high interactive condition did not perform better in the subsequent C-Span working memory measure than those in the low interactivity condition, M_{high}= 17.39, SD = 10.93, M_{low} = 24.52, SD = 9.86, $t(59)$ = -1.47, p = .147.

Cross-experiment Comparison

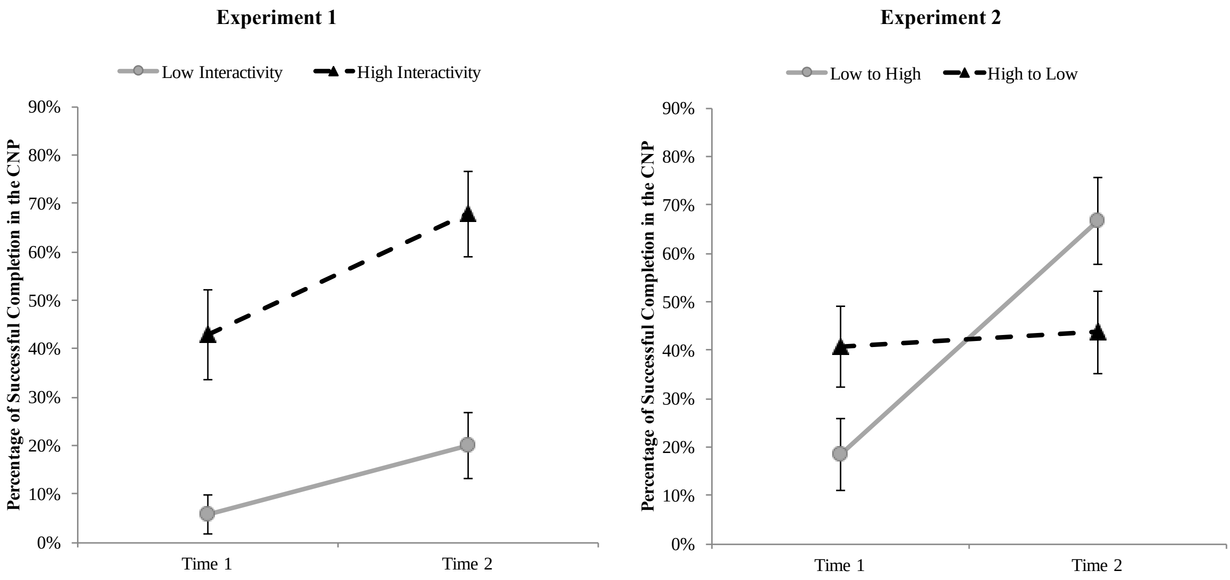

Figure 4.2: Line graph displaying percentage of successful completion in the CNP across both experiments.

The switch in the level of interactivity substantially affected performance, demonstrated in Figure 4.2. This is most apparent in when comparing results across experiments. Among the participants who did not solve the CNP in a low interactivity condition in Experiment 1 at Time 1, 5 (or 15%) solved the problem at Time 2. In Experiment 2, of the participants who did not solve the problem at Time 1 in a low interactivity condition, 14 (or 56%) now solved the problem when they were switched to a high interactivity condition at Time 2, a significant improvement in performance, $\chi^2(1, N = 56) = 12.64$, $p < .001$. Conversely, the switch to a low interactivity condition for participants who started in a high interactivity condition depressed performance considerably. Of the 20 participants who failed to solve the problem at Time 1 in Experiment 2 in the high interactivity condition, only 1 (or 5%) solved it at Time 2 in the low interactivity condition. In Experiment 1, of the 16 participants who had not solved the problem at Time 1 in the high interactivity condition, 7 (or 44%) solved it at Time 2, a significant difference, $\chi^2(1, N = 36)$

= 7.22, p = .007. In addition, across experiments, the difference in solution rate between the high interactivity condition at Time 2 in Experiment 2 (61%) and the solution rate in the high interactivity condition at Time 1 in Experiment 1 (43%) was not significant, $\chi^2(1, N = 51)$ = 1.64, p = .20. Because two of the four cells of the contingency table had expected frequencies lower than five, a Fishers exact test was also conducted. This was significant, p = .012, supporting the initial chi square test.

Table 4.4.

Performance improvements in Experiments 1 and 2 following an incubation period, as a function of the initial (Time 1) and final (Time 2) level of interactivity.

	Final interactivity level			
Initial interactivity level	low		high	
	M	*S.E.*	*M*	*S.E.*
low	+14%	0.03	+52%	0.04
high	+3%	0.03	+25%	0.04

Taken together, these results support the enactment-driven hypothesis shown in table 4.2. As demonstrated in table 4.4, switching from a high interactivity level to a low interactivity one resulted in much lower increases in performance compared to switching from a low interactivity level to a high interactivity one later.

Discussion

In Experiment 2, participants' task environment was changed after the two-week incubation period. Those who started in the high interactivity version at Time 1 switched to a low interactive version at Time 2. Those who started in the low interactivity condition at Time 1 changed to the high interactivity condition for Time 2. Upon first encounter, participants were more likely to successfully complete the CNP in the high interactivity condition, echoing the findings of Experiment 1. After the incubation period, performance for participants who started in the low interactivity condition then switched to high interactivity was significantly better than participants who started high then switched to low. This difference in performance at Time 2 is opened to at least two interpretations. It could be that experience with the problem in a high interactivity condition does not help participants engage in a conceptual reflection on the problem. Thus, when moved to a low interactivity condition later, participants solve the problem as if it's their first attempt. Alternatively, struggling to solve the problem in a low interactivity condition may force participants to gain a deeper conceptualisation of the task. Reencountering the problem later in a high interactivity context, participants are better able to translate that knowledge in a set of actions, which produces a correct solution. More generally, this finding suggests that the incubation effect at Time 2 is primarily realised through enactment rather than through a representation change achieved prior to working on the task a second time. Indeed, if incubation facilitated insight through a mental representation change rather than enactment through interacting with the task, then performance should not be affected by the level of interactivity afforded by the task at Time 2. The cross-experiment comparison reveals, however, that performance is affected by the level of interactivity at Time 2.

Pooling the data across conditions, those who had better long-term memory were most likely to complete the CNP at Time 2. This suggests that long-term memory might be implicated in moderating the incubation effect by facilitating performance when the task environment after incubation is switched. Working memory capacity as measured with the C-Span test did not predict performance, nor differed across conditions. Participants who increased from low interactivity to high interactivity measured best in the C-Span working memory test. However, this effect is not an effect of order, but the level of interactivity afforded prior to the C-Span testing. Although the C-Span scores differed slightly between successful and unsuccessful problem solvers and interactivity levels, working memory did not significantly differ among participants in this experiment.

General Discussion

The experiments presented in this chapter investigated incubation and interactivity in insight problem solving using the CNP. Performance between conditions was measured as participants either successfully solving the problem or not, in addition to time taken to reach the correct solution. To measure the effect of incubation, participants were asked to reattempt the CNP after a two-week break. In Experiment 1, participants attempted the task after an incubation period with the same level of interactivity as their initial encounter. In Experiment 2, their level of interactivity switched at Time 2; they moved from low interactivity to high interactivity, or from high interactivity to low interactivity. As expected, in both experiments participants who had the opportunity to think in an environment that afforded high levels of interactivity achieved insight more frequently. The results were in line with others showing that cognitive interactivity enhanced insightful solutions (Fioratou & Cowley, 2009; Vallée-Tourangeau et al., 2015; Vallée-Tourangeau et al., 2016b; Weller et al., 2011). Focusing on initial performance, the overall solution rates in both Experiments 1 and 2 are higher than Fioratou and Cowley (2009, Experiment 1) who reported only one (3%) of their participant completed the problem in the low interactivity condition and ten (33%) in the high interactivity condition. The difference may be explained by the length of time participants could spend attempting to solve the task. Fioratou and Cowley allowed a maximum of 10 minutes to complete the CNP, whereas the present experiments allowed participants to spend up to 30-minutes to attempt solutions. Also, the average time in the present experiments was longer than 10-minutes indicating that 10-minutes may not have been enough to allow all potential solvers to reach the solution. Solution latencies were not measured by Fioratou and Cowley, therefore, it is not possible to make any further comparisons without implementing the same time restrictions. Nonetheless, both the results of Fioratou and Cowley and the present experiments support the notion that insightful solutions are supported through a higher interactivity environment, despite the difficulty of the CNP.

Performance following incubation generally improved both in terms of solution frequencies and latencies. All participants who found the solution at Time 1 successfully transferred their solution at Time 2. In Experiment 1, the two-week break led to more participants producing the correct solution to the problem regardless of the level of interactivity afforded. Even in the more challenging low interactivity condition, a break in active engagement promoted insight. In other words, the incubation effect did not differ as a function of the level of interactivity. However, in Experiment 2, the level of interactivity played a crucial role in insightful performance following the incubation period. Participants who could not solve the problem in the low interactivity level at Time 1 were most likely to overcome their impasse when attempting the CNP with a high level of interactivity at Time 2. By contrast, those working on a high interactivity version at Time 1 were not able to overcome their impasse at Time 2 when limited to the low interactivity version. Encountering a richer representation of the problem first did not facilitate insight when thinking was later constrained to deductive processing in a low interactive environment later. The cross-experiment comparison confirmed this.

The large improvement in performance following the incubation period was a function of initial difficulty, in line with Knoblich et al. (1999), where those serving in the low interactivity condition at Time 1, in both experiments, were placed in the most difficult condition. By contrast, reducing the level of interactivity, moving from high to low, may have hindered the effect of incubation. Attempting the most difficult version of the problem first allowed for substantially improved subsequent performance, where participants may have removed self-imposed inappropriate representations of the task (Fioratou et al., 2010; MacGregor et al., 2001; Ormerod et al., 2006).

Limited to using largely internal cognitive resources and deductive processing, participants might have been forced to conceptualise and deeply consider the CNP. In other words, when placed in a low interactivity condition, participants gain a better mental representation of the problem and what it requires them to do. Nonetheless, most fail to successfully reach insight. At Time 2, the provision of the metal chains in a high interactivity environment afforded participants' the ability to express and explore their mental representations: They restructure, reconstruct and interact with the metal chains. This creates a dynamic environment, where interactions with the chains are less random, driven by a conceptualised goal. On the other hand, those who began Time 1 in the high interactivity condition then restricted to a low interactive condition at Time 2 showed no improvement in insight performance yet all participants who found the solution were able to reproduce it later. Reducing the level of interactivity afforded limited new insightful solutions but did not limit the ability to transfer a learnt solution. This may be because problem solvers returned to the same problem following at Time 2. It would be interesting to explore whether these trends of results are replicated when a new problem is introduced later.

If an incubation effect is partly driven by adopting a fresh perspective when later returning to the problem, it would be expected that long-term memory scores would be implicated in insightful solutions at Time 2. The long-term memory scores revealed that participants who were able to remember more facts about the Sun were not more likely to benefit from the incubation period in Experiment 1. Although the long-term memory decline was slightly less steep among those who solved the problem in Experiment 2, the difference was marginal. Therefore, long-term memory scores did not account for the incubation effects observed across experiments. However, working memory was associated with insight performance. In Experiment 1 when participants were constrained to paper-and-pencil higher working memory capacity influenced insight performance. Although this finding is not replicated in Experiment 2 when participants attempt the CNP in both a low and high interactivity condition, working memory capacities may moderate solutions for low interactivity problems.

The results reported in this chapter confirmed that increasing the interactivity of a problem solver's immediate environment facilitates insight. Further, taking a break from a problem and returning to it later enables insightful solutions. Specifically, an incubation effect only manifests when the task environment remains the same (Experiment 1), or when the level of interactivity is increased (Experiment 2). Thus, insight through interactivity fosters stronger performance on both the initial and subsequent task. Importantly, the effect of incubation manifests most when problem solvers experience a high level of interactivity at Time 2. The following chapter seeks to explore what happens when the subsequent task is different.

Chapter 5: Interactivity and Transfer

When confronted with a problem, mapping previously learnt information to that problem is known as transfer (Mayer, 1992). As we have already reviewed in Chapter 2 (p. 36) previously acquired knowledge can be influential when solving a new problem. Typically, transfer is investigated when researchers present problem solvers with a source problem to solve, or a story, which hosts relevant information they can draw analogies from. Subsequently, the problem solvers are given a target problem; a new yet similar problem to solve, which draws upon information learnt from the source. While some evidence has shown that transfer is possible (e.g., Chen, 2000; Gick & Holyoak, 1980; 1983; Knoblich et al., 1999), most problem solvers find it difficult to effectively apply source information to the target problem (e.g., Detterman, 1993; Greeno, 1974; Hayes & Simon, 1997; Lave, 1988; Reed et al., 1974). This is often because solvers fail to notice the similarities, so a noticeable connection between the target and source is important (Chen, 2002). Yet, even when the problems share sufficient similarity, problem solvers often fail to spontaneously transfer, which is to implement the information taken from the source into the target problem (Chen & Daehler, 2000). Transfer can be supported by giving participants a hint such as telling them explicitly that the source information is useful to solve the target problem (Bowden, 1985; Fioratou et al., 2010). The hint allows them to move through the problem space more efficiently where they can scaffold their thinking on what they learnt from previous information.

The Matchstick algebra problems (Knoblich et al., 1999, see Chapter 2, p. 18), which contained false Roman numerals arithmetic expressions were presented to problem solvers in two separate blocks exploring transfer. The problems ranged in complexity and difficulty, increasing from Type A to Type D. Initially, six false expressions are attempted, which were presented in a random order. Then, their participants attempted to make another six expressions true. Performance, measured by how many expressions were made true correctly and how quickly they did so, was reported to be better in the second block. A transfer effect where a solution was self-generated in the first instance allowed participants to find solutions more often and much quicker. Specifically, the hardest 'Type D' problems, which required problem solvers to change a '**X**' into a '**V**' were solved more frequently in the second block.

Using an interactive version of the Matchstick problems in which problem solvers could physically move a single matchstick, Weller et al. (2011, see Chapter 3, p. 66) reported similar findings to Knoblich et al. Specifically, the hardest 'Type D' problems were solved as frequently as the easiest 'Type A' problems only when participants could enact a solution. Therefore, interactivity facilitated insight. Although the same 12-expressions were used in both investigations, high solution rates were reported for the Type D problems as both a transfer effect (Knoblich, et al., 1999) and an enactment effect (Weller et al., 2011). It could be suggested that interactivity is as effective as self-generated transfer for promoting insight in the Matchstick algebra problems. The experimental paradigm of these experiments do not easily lend themselves to a comparison. Nonetheless, this raises the question as to whether interactivity or transfer is most effective for enhancing insight.

Much of the research exploring transfer does not require participants to come up with a solution by themselves. They are given a solution to a problem or a narrative, and then they have to apply this to a new situation. But they haven't laboured the thinking in the first instance. Perhaps transfer would be more efficient (i.e., participants would be better able to notice similarities by themselves without hint) if participants actively work towards a self-generated solution at first in the source problem. In light of this, the current chapter explored transfer when solutions are self-generated. Thus, problem solvers actively engaged with the source problem then attempted a target problem, without any hints or feedback on performance. Two experiments were designed using the Cheap Necklace Problem to explore whether spontaneous transfer will occur, and whether interactivity or transfer (or both) is more efficient for insight.

Experiment 3

Experiment 3 investigated the role of interactivity and transfer in the CNP when the problem presentation remains the same throughout. It was expected for the effect of increasing interactivity on performance observed in Experiments 1 and 2 to be replicated: manipulating the physical elements of the problem should yield better performance than mentally simulating moves. To investigate transfer, a new variant of the CNP was introduced. The new variant (CNP-V2, see Figure 5.1), adapted from Fioratou (2005), consisted of two 4-link chains and two 2-link chains. Both versions require breaking one smaller chain into individual links, then using those links to create a complete necklace.

You are given four separate pieces of chain; the first two chains are four links in length and the last two chains are two links in length. It cost 2¢ to open a link and 3¢ to close a link. All the links are closed at the beginning of your problem. Your goal is to join all 12 links of chain into a single circle at a cost of no more than 15¢.

Figure 5.1. The new variant Cheap Necklace Problem, which was used as the target problem.

Participants started by working on the standard version (CNP-V1, the source problem) of the CNP, then following a break, worked on the new variant (CNP-V2, the target problem). The target problem shared superficial, structural, and procedural similarities with the source problem, which is a pre-requisite for successful transfer (Chen, 2002). Further, transfer had already been observed to occur across the two tasks, albeit to a limited extent

(Fioratou, 2005). To investigate the degree to which interactivity may impact transfer, participants attempted both versions in either a low or high interactivity condition. While several studies note the importance of hints, explicitly alerting participants to the link between the source and target problem (e.g., Gick & Holyoak, 1980; Lave, 1988), it is not clear whether a hint is important for a problem that shares sufficient similarity, and where solutions are self-generated. Thus, in the present experiment, participants were not given the solution to CNP-V1 (the source problem), nor were they made aware of the usefulness of source solution through any hints. This allowed for experimental control where the effect of interactivity, and only interactivity, can be shown in transfer. It was expected for successful transfer to be observed, with participants being able to produce insightful solutions for CNP-V2 having found a solution in CNP-V1. It was further predicted that the rate of transfer would distinctly vary as a function of the level of interactivity.

Together with solving the target problem, transfer was measured by any improvements in the efficiency of solving the task compared to the source. These improvements may be observed in a more effective solution path (e.g., using fewer moves, see Guthrie, Vallée-Tourangeau, Vallée-Tourangeau, & Howard, 2015) and/or improvement in latencies to solutions (Knoblich et al., 1999). Therefore, latencies to solution as an effect of transfer were measured. As working memory capacity was associated with performance in the CNP in the previous experiments (see Chapter 4), Experiment 3 sought to determine whether interactivity will have an effect on working memory performance, using a forward and backward digit span (Baddeley, 2005).

The dual process theory of thinking, which Stanovich and West (1999) called system 1 and system 2 processing, refers to how we process and make decisions on information we are presented. The system 1 process is quickly executed thoughts, which are spontaneous and require little attention. In contrast, system 2 process is more deliberate and more conscious thought process. When considering the Cheap Necklace Problem and the initial moves made by participants, it is possible that the system 1 process drives participants to join the ends of the chains together, as this is an intuitive move when “making” a necklace. However, when participants take the time and follow a more deliberative thought process, namely system 2, they are able to navigate towards a solution. However, not all participants may reflective enough to move away from the intuitive maximising strategy of joining the ends of the chains together. Using the cognitive reflection test (Frederick, 2005), participants’ ability to override their intuitive response can be measured to explore an association with insightful solutions in the CNP. Further, as a means of discovering additional factors that may correlate with insightful performance in the CNP, three additional exploratory measures were taken. Namely, impulsivity using Barratt impulsiveness scale-11 (Barratt, 1965) was measured to explore whether participants who act without thinking (i.e., who act more impulsively) are more likely to find the solution by engaging more in an inductive processing loop. Additionally, as the CNP can be interpreted as a numerical problem and does require some basic numeric ability to keep a track of how much has been spent, numeracy was measured by a subjective numeracy scale and numeric anxiety was assessed through a self-report maths anxiety scale (Ashcraft & Kirk, 2001). The choice to include these measures was not theoretically driven. They were included to explore whether these individual differences could moderate the results. As such, there were no explicit hypotheses.

Method

Participants. Seventy-six participants from Kingston University volunteered to participate in exchange for research participants’ credits. They consisted of 62 females, M_{age} = 22.54, *SD* = 6.33. All participants were naïve to the Cheap Necklace Problem prior to participation.

Materials. A seven-page problem pack was presented to all participants, one page at a time. The first page of the pack was an informed consent and video release form. Next, in both low and high interactivity conditions, the pack included the instructions for the standard CNP (CNP-V1) on a sheet of paper. The next two pages separately presented the Cognitive Reflection Task (CRT) which asked them to note answers to three riddle style questions. The questions appear to be simple to answer (e.g. a bat and a ball cost £1.10 in total, the bat cost £1 more than the ball, how much was the ball?), but they require deliberation and logic to answer correctly. The fourth page was the Barratt's Impulsiveness Scale-11 (BIS), a 6-response Likert scale with 30 questions (adapted from Barratt, 1965). Then on the fifth page, the instructions for the new variant CNP (CNP-V2) were presented. Finally, on the last two pages, participants were presented with the Subjective Numeracy Scale questionnaire (NS), a 6-response Likert scale with eight questions followed by a Maths Anxiety Scale questionnaire (MAS), a 5-response Likert scale with 23 questions (adapted from Ashcraft & Kirk, 2001). An additional recording sheet was used by the experimenter to record participants' answers on the Forward Digit Span (FD-Span) and Backward Digit Span (BD-Span) working memory test (adapted from Baddeley, 2005). The working memory tests required participants to recall a set of numbers that the researcher read aloud to them. The set of numbers began with just two numbers, which increased every other set until the sets were eight numbers in length in the FD-Span and five numbers in length in the BD-Span. Lastly, a debrief sheet was handed out to participants.

In the high interactive condition, participants were also given four metal chains to represent the information in the CNP they were working on. For the CNP-V1, these were the same as Experiments 1 and 2. For the CNP-V2, these consisted of two 4-links chains and two 2-links chains (see Figure 5.1). In the low interactivity condition, participants were only provided with a pen for both CNP versions.

Design and Procedure. This experiment employed a 2 x 2 mixed design, where the between-subject factor was the level of interactivity (low interactivity, high interactivity) and the CNP version was a within-subject factor (CNP-V1, CNP-V2). Participants were randomly allocated to a low or high interactivity condition and completed both CNP-V1 and CNP-V2 with the same level of interactivity.

All testing was conducted individually in an observation lab. Once participants consented to participate, having read and signed the informed consent form, they were presented with the standard version of the CNP and the experimenter read the instructions aloud (shown in Figure 5.2). Participants in the low interactivity condition were provided a pen to write notes as they solved the problem. Those in the high interactivity condition were presented with the metal chains and were shown how to open and close them. High interactivity participants were not provided a pen at this stage. For those who consented to be recorded, the cameras were turned on once they were ready to start working on the problem. There was a maximum of 15 minutes to complete this task, with participants required to carry on until they had completed the task, or they'd reached 15 minutes[2]. Once they were ready to announce their answer, the time taken to complete the problem was noted. Participants in the high interactivity condition were then given a pen so they could write down their solution. The cameras were then turned off. Participants were then given the CRT, with no time restraint to answer the three questions. Then, they completed the BIS with no restraint. Next, they were presented with the new variant CNP in same condition as they attempted standard

[2] Chapter 4 revealed that some participants were more diligent than others in attempting to find a solution, specifically in the high interactivity condition. Diligence also predicted performance upon the second encounter of the same problem. To control for this potential mediating effect on transfer, participants in the present study were instructed to persevere until they found the correct solution. To avoid fatigue, participants were permitted 15-minutes for each problem, as the average successful completion for those in the previous experiments was 12-minutes, with no participants taking longer than 20-minutes.

version. Again, participants were permitted a maximum of 15 minutes to complete this task, with low interactivity participants given just a pen and high interactivity conditions given a set of metal chains that represented the problem. The cameras were turned on, if permitted by consent. Once they were ready to announce their answer, the time taken to complete the problem was noted. Participants in the high interactivity condition were given a pen at this point to write their answer down on the problem sheet. The video recording was stopped. Participants were then asked to complete a NS followed by the MAS with no time restrictions. Next, the researcher conducted the FD-Span by reading a set of numbers, which the participants were asked to recite in the exact same order they were read to them. Then, the BD-Span was completed, which required participants to recite a different set of numbers in reverse order. Lastly, they were debriefed and provided with feedback on their performance.

Results

The primary objectives of this experiment were to assess whether the level of interactivity afforded by the task would affect insight, and whether spontaneous transfer would occur. Latency to solution, the time it took participants to reach the correct solution, was also used as a measure of the impact of transfer. The FD-Span and BD-Span working memory measures were used to determine whether the cognitive resources available accounted for performance. The cognitive reflection test was used to explore whether performance between groups was due to participants' ability to reflect better on the task. In addition, some further individual differences were measured to explore other factors that may affect insight and transfer. These were impulsivity, numeracy and maths anxiety.

Cheap Necklace Problem Performance

Correct solution to the Standard Version (CNP-V1) was classified as deconstructing one of the four chains, identifying three individual links, which were used to connect the remaining three chains. Successful performance for New Variant (CNP-V2) was classified as deconstructing one of the two-linked chains and opening the end of one of the four-linked chains, which are used to connect the remaining chains into a complete necklace.

Solution Rates. The frequency of solutions was assessed, with solution rates reported in Table 5.1: Fourteen (or 37%) of the participants solved the problem in the high interactivity condition in CNP-V1, while 6 (or 16%) solved the problem in the low interactivity condition. The difference in solution rates was significant, $\chi^2(1, N = 76) = 4.34$, $p = .037$. Of the 20 participants who solved CNP-V1, 18 were able to solve CNP-V2; one participant in each the low and high interactivity was unable to transfer their solution. Of the 24 participants who had not solved CNP-V1 in the high interactivity condition, 6 (or 25%) solved CNP-V2; of the 32 participants who were unable to solve CNP-V1 in the low interactivity condition, 4 (or 13%) solved CNP-V2. This difference was not significant $\chi^2(1, N = 56) = 1.46$, $p = .227$.

Table 5.1.

Solution frequencies in the low and high interactivity condition for CNP-V1 and CNP-V2, along with solution latencies (in seconds).

	Low Interactivity				**High Interactivity**			
CNP-V1	Yes		No		Yes		No	
Freq	6		32		14		24	
%	16%		84%		37%		63%	
Latency to Solution								
M	543.3				433.1			
SD	227.5				202.9			
CNP-V2	Yes	No	Yes	No	Yes	No	Yes	No
Freq	5	1	4	28	13	1	6	18
%	83%	17%	13%	87%	93%	7%	25%	75%
Latency to Solution								
M	200.4		601.8		271.5		555.5	
SD	88.7		223.5		206.0		184.9	

Performance Analysis. To further explore the effects of interactivity and transfer, and their potential interaction, an additional performance analysis was completed. A 2 × 2 Mixed ANOVA tested for the between-subject effect of level of interactivity (low interactivity, high interactivity), and the difference in performance between CNP-V1 and

CNP-V2 as the within-subject factor with CNP performance scored as 0 = never solved, 0.5 = solved one version, 1 = solved both versions. Across both versions, the level of interactivity offered by the metal chains significantly increased overall performance: M_{high} = .43, *SD* = .45, M_{low} = .19, *SD* = .36, $F(1, 74) = 6.38$, $p = .014$. Participants were also able to transfer their learnt solution across version and a significant proportion of those who were unable to complete CNP-V1 were able to complete CNP-V2 as performance between versions improved: $M_{CNP\text{-}V1}$ = .26, *SD* = .44, $M_{CNP\text{-}V2}$ = .37, *SD* = .49, $F(1, 74) = 5.61$, $p = .020$. However, the improvement in performance across versions did not vary as a function of interactivity level, $F(1, 74) = .351$, $p = .556$.

Latencies. The time taken to arrive at a correct solution was taken to measure the effect of interactivity and transfer. It was predicted that latencies to solution would improve through time as an effect of transfer, where insight will be achieved quicker for CNP-V2 than CNP-V1. For those who successfully completed both versions, latencies to solution were considerably lower in CNP-V2 compared to CNP-V1: $M_{CNP\text{-}V1}$ = 466.20, *SD* = 210.92, $M_{CNP\text{-}V2}$ = 366.86, *SD* = 239.77. In a 2 (low interactivity, high interactivity) × 2 (CNP-V1, CNP-V2) Mixed ANOVA in which CNP performance was scored as 0 = never solved, 0.5 = solved one version, 1 = solved both versions, the main effect of CNP version was significant, $F(1, 18) = 6.13$, $p = .023$, but the main effect of level of interactivity, $F(1, 18) = .335$, $p = .570$, and the interaction between CNP version and Interactivity, $F(1, 18) = .626$, $p = .439$, were not. In other words, even though the level of interactivity did not affect how quickly a solution was found, latencies to solution did improve across time as a function of transfer.

Working Memory Performance

As working memory was associated with insightful performance in Experiments 1 and 2, participants' working memory capacity was measured by their performance on a Forward and Backward Digit Span test. As the cognitive effort required to complete the FD-

Span is different to the BD-Span (Baddeley, 2003), the two were analysed separately, providing two working memory measures.

Forward Digit Span. Pooling the data across conditions, participants who solved at least one version of the problem generally had higher FD-Span scores than those who did not solve the problem: M_{Solved} = 11.23, *SD* = 2.10, $M_{\text{NotSolved}}$ = 10.35, *SD* = 2.44. However, a regression analysis indicated that participants' performance on the CNP (scored as 0 = never solved, 0.5 = solved one version, 1 = solved both versions) could not predicted by FD-Span, $b = .04$, $SE = .02$, $t(74) = 1.63$, $p = .107$.

To explore whether low interactivity burdened working memory, FD-Span scores were compared between interactive conditions. Those who attempted the CNP in the low interactivity generally had lower FD-Span scores: M_{low} = 10.01, *SD* = 2.20, M_{high} = 11.32, *SD* = 2.24. An independent sample t-test showed those who completed the CNP in a high interactive condition performed significantly better in the subsequent FD-Span working memory measure compared to those in the low interactive condition, $t(74) = -2.38$, $p = .020$, $d = .39$.

Backward Digit Span. Similar to the results reported above, participants who solved at least one version of the problem generally had higher BD-Span scores than those who did not solve any version: M_{Solved} = 7.03, *SD* = 1.96, $M_{\text{NotSolved}}$ = 6.13, *SD* = 1.85. A regression analysis indicated that successful completion of at least one version of the CNP could be predicted by BD-Span scores, $b = .06$, $SE = .03$, $t(74) = 2.04$, $p = .045$.

To explore whether low interactivity burdened BD-Span scores, they were compared between interactive conditions. Those who attempted the CNP in the low interactivity generally had lower BD-Span scores: M_{low} = 6.00, *SD* = 1.83, M_{high} = 6.97, *SD* = 1.92. An independent sample t-test showed those who completed the CNP in a high interactive condition performed significantly better in the subsequent BD-Span working memory measure compared to those in the low interactive condition, $t(74) = -2.26$, $p = .027$. This suggests that the first result (i.e. higher BD-Spans were associated with better performance) could be due to the fact that people performed better on the CNP in the high interactivity condition and also performed better on the BD-Span test after completing the CNP in this condition. Thus, the key factor in facilitating performance may not be people's working memory capacity, but rather whether they completed the CNP in a highly interactive environment.

Individual Differences Measures

Participants' ability to reflect and override their initial responses was measured using Frederick's (2005) cognitive reflection test (CRT). Further, as a means of discovering additional factors that may correlate with insightful performance in the CNP, individuals were profiled on: impulsivity using Barratt impulsiveness scale-11 (BIS), numeracy measured by a subjective numeracy scale (NS), and numeric anxiety assessed through a self-report maths anxiety scale (MAS). As these individual differences were exploratory, there were no explicit hypotheses. The correlations with performance across conditions are shown in Table 5.2.

Table 5.2.

Means, Standard Deviations, and Correlations of the Individual Difference Measures.

			Measure			
Cheap Necklace Problem	M	SD	CRT	BIS	NS	MAS
Overall	0.32	0.42	.27*	-.01	.08	.03
Low Interactivity	0.19	0.36	.35*	-.21	.13	-.08
High Interactivty	0.43	0.45	.24	.08	-.02	.14

* $p < .05$

Cognitive Reflectivity. Across both conditions (low interactivity and high interactivity) and average CNP performance between versions (0 = never solved, 0.5 = solved one version, 1 = solved both versions), a Pearson's correlation coefficient indicated CNP performance correlated significantly with CRT scores (0 – 3), *r* = .27, *p* = .017. Specifically, higher CRT scores correlate with higher performance average in the CNP. To explore whether the level of interactivity was associated with CRT scores, the interactive conditions were assessed separately. A positive correlation between CRT and performance average was observed among those who completed the CNP in the low interactivity condition, *r* = .352, *p* = .030. However, there was no correlation for high interactivity participants, *r* = .242, *p* = .143. To further explore these findings, a multiple regression was conducted where level of interactivity (-1 = low interactivity, 1 = high interactivity) and CRT scores (0 – 3) were predictors and the overall performance across both versions (0, 0.5, 1) as the outcome variable. The regression confirmed participants' CRT scores significantly predicted performance in the CNP, *b* = .12, *SE* = .05, *t*(74) = .244, *p* = .017. Further, the effect of CRT scores on CNP performance varied as a function of interactivity level, *b* = .46, *SE* = .18, *t*(74) = 2.54, *p* = .0.13 (see Table 5.4). In other words, the need to override an intuitive response could predict insightful performance in the CNP. However, this need is diminished in a high interactive environment.

Table 5.3.

Regression Analysis Summary for CRT and Interactivity Predicting Insight Performance.

Variable	*B*	95% CI	ß	*t*	*p*
		Outcome: CNP Performance			
CRT	0.12	[.02, .21]	0.27	2.44	**.017**
CRT × Interactivity	0.46	[.10, .81]	0.28	2.54	**.013**

Note. R^2 for Overall Performance = .156

Impulsivity. Across both conditions, a Pearson's correlation coefficient indicated average CNP performance did not correlate with impulsiveness, *r* = -.01, *p* = .940. To explore whether impulsivity correlated with performance when data was not pooled across conditions, low and high interactivity participants' BIS scores were assessed separately.

However, performance in the CNP did not correlate with impulsivity for low interactivity participants, $r = -.21$, $p = .206$, or high interactivity participants, $r = .08$, $p = .625$. Thus, impulsivity is not associated with successful completion of the CNP.

Numeracy. Overall, a Pearson's correlation coefficient indicated average CNP performance did not correlate with the numeracy, $r = .01$, $p = .485$. Dividing numeracy scores between high and low interactivity participants, there was no correlation with the low interactivity participants, $r = .13$, $p = .423$, or those who completed the CNP in the high, $r = -.02$, $p = .895$.

Maths Anxiety. Overall, a Pearson's correlation coefficient indicated CNP performance did not correlation with the MAS, $r = .03$, $p = .806$. Performance in low interactivity did not correlate with MAS, $r = -.08$, $p = .655$, nor did high interactivity, $r = .14$, $p = .289$.

Discussion

Experiment 3 examined the role of interactivity and transfer across two versions of the Cheap Necklace Problem. Performance was significantly better when participants were given metal chains that represented the problem in the high interactivity condition, compared to those restricted to solving the problem in the low interactivity paper-and-pencil condition. This trend was observed across both versions of the CNP. Further, more people were able to solve the new variant, which served as the target problem in this experiment, and participants who solved both versions completed the CNP-V2 quicker. Therefore, performance improved across versions. Of those participants who found the solution to CNP-V1, most were able to transfer their learnt solution across to CNP-V2. In addition, among participants who failed to generate a solution to CNP-V1, some were able to produce the correct solution to CNP-V2. Although the increased level of interactivity was an important determinant for insight since insightful performance was better in the high interactivity condition, increased interactivity did not lead to larger rates of transfer in CNP-V2.

Working memory, in part, played a role in explaining performance in the CNP. Though higher scores in the Forward Digit-Span did not make a participant more likely to solve either version of the problem, higher Backward Digit-Span scores were associated with better performance in both high and low interactivity conditions, suggesting that executive control capacity was a key predictor. Moreover, both the FD-Span and BD-Span working memory scores were lower for participants in the low interactivity condition compared to those in the high interactivity condition. This suggests that attempting to solve the CNP under low interactivity conditions is cognitively taxing. In addition, cognitive reflection was also associated with insight, specifically for those experiencing the problem in the low interactivity condition. This suggests that the ability to engage in reflective thinking is most beneficial under low interactivity. However, there were no correlations with insight performance with impulsivity, numeracy or maths anxiety.

Participants received no hints to help them engage in a productive path to solution, however they generated a solution to the source problem (CNP-V1). Under these circumstances, the rate of successful transfer was very high as only two participants were unable to transfer their solution to CNP-V2. These findings emphasise the importance of similarity for effective transfer. More important, self-generated insight allowed almost all participants to transfer their solution *without* a hint. In addition to successfully completing CNP-V2, participants were more efficient, as they found the solution much quicker. Solutions to CNP-V2 were found more frequently than CNP-V1. Although the increase in solution rates across versions were not significant, they are interesting to note. These improvements across version cannot be explained by transfer; if a participant didn't find the solution to CNP-V1 nor provided feedback on their attempt, they had no solution to transfer. It is possible that they were able to take across some information they learnt while attempting CNP-V1, such that joining the ends of each chain together doesn't work, which gave them a smaller problem space within which they could search for a solution. Alternately, the break between CNP-V1 and CNP-V2 may have helped them overcome an impasse through an effect of incubation. As observed in Experiment 1, when participants reach an impasse, a break from active engagement in the task helps boost a solution when returning to the problem.

The findings of Experiment 3 indicate that higher levels of interactivity do not facilitate transfer, raising the question of whether a change in subsequent problem presentation may be implicated in changes in performance across versions. Considering the findings reported in Experiment 2, a fourth experiment was devised to address this question.

Experiment 4

In Experiment 3, the task environment significantly impacted on performance across both versions of the CNP. Even though transfer was evident across both interactivity conditions, this did not vary as a function of interactivity level. Thus, the high interactive version created a task environment in which participants could find the solution to CNP-V1 more frequently, but there was no benefit to transfer. By contrast, the low interactivity task environment meant lower solution rates, but it did not hinder transfer abilities. This raises the question of what drives transfer and improvements across versions; is it more important to start in a high interactive task environment, or end with interactivity?

In line with Experiment 2 (see Chapter 4), solutions to CNP-V2 could be determined by restructuring on a richer, more dynamic representation of the problem (transfer-driven insight) or by restructuring through enactment on the metal chains (enactment-driven insight). Transfer-driven insight would predict performance in a paper-and-pencil task in CNP-V2 following a high interactive CNP-V1 will remain high. By contrast, experiencing the low interactivity CNP-V1, which is less amenable to restructuring, may offer a limited opportunity for performance to improve in CNP-V2. Therefore, starting with the high interactive environment is most beneficial. Alternately, if performance improvement is enactment-driven, working in a low interactive task environment during CNP-V1 would impede subsequent performance, even when working in the richer, more dynamic representation if the CNP in CNP-V2. By contrast, experiencing the high interactive task environment first should afford the possibility for vast improvements in performance for CNP-V2 (see table 5.4). Thus, under this hypothesis, ending with the high interactive environment would be most important.

Table 5.4.

Transfer-driven vs Enactment-driver performance in CNP-V2 on the CNP. CNP-V1 = Initial Interactivity level, CNP-V2 = Final Interactivity level.

[1]*Denotes small (+) or large (++) increase in performance observed in Experiment 2.*

[2]*Denotes small (+) or large (++) increase in performance expected in Experiment 3, under the (a) transfer-driven or the (b) enactment-driven hypothesis, respectively.*

a) Transfer-driven performance insight in CNP-V2

	Final interactivity level	
Initial interactivity level	low	high
low	+[1]	+[2a]
high	++[2a]	++[1]

b) Enactment-driven performance insight in CNP-V2

	Final interactivity level	
Initial interactivity level	low	high
low	+[1]	++[2b]
high	+[2b]	++[1]

Method

Participants. Seventy-four participants from Kingston University volunteered to participate in exchange for research participants' credits. The participants consisted of 59 females, M_{age} = 24.70, *SD* = 6.70. All participants were naïve to the Cheap Necklace Problem prior to participation.

Materials. The same materials eight-page problem pack from Experiment 3 was used in this experiment.

Design and Procedure. Experiment 4 employed a 2 × 2 mixed design, with a within-subject factor of Version (CNP-V1, CNP-V2) and trend of interactivity level experienced as the between subject factor (low to high interactivity, high to low interactivity). All participants initially attempted to solve the CNP-V1, in either a low interactivity or a high interactivity condition, and then attempted the CNP-V2 with the different level of interactivity.

Results

Cheap Necklace Problem Performance

Solution Rates. Solution rates are reported in Table 5.5: Sixteen (or 42%) of the participants who solved the problem in the high interactivity condition in CNP-V1, while 6 (or 17%) solved the problem in the low interactivity condition. The difference was significant, $\chi^2(1, N = 74) = 5.73$, $p = .017$; this pattern of solution rates replicates the pattern observed in Experiment 3. All but one participant who solved CNP-V1 in the high interactivity condition was able to solve CNP-V2 in the low interactivity condition. Of the 22 who did not solve CNP-V1 in the high interactivity condition, just one (or 5%) was able to solve CNP-V2 in the low interactivity condition. All participants who solved CNP-V1 in the low interactivity condition were able to solve CNP-V2 in the high interactivity condition. Of the 30 who did not solve CNP-V1 in the low interactivity condition, 11 (or 37%) were able to solve CNP-V2 in the high interactivity condition. While fewer solved the problem in the low interactivity condition (16, or 42%) than in the high interactivity condition in CNP-V2 (17, or 47%), the difference was not significant, $\chi^2(1, N = 74) = .196, p = .658$.

Table 5.5.

Solution frequencies in the low and high interactivity condition for CNP-V1 and CNP-V2, along with solution latencies.

	Low Interactivity				High Interactivity			
CNP-V1	Yes		No		Yes		No	
Freq	6		30		16		22	
%	17%		83%		42%		58%	
Latency to Solution								
M	601.3				565.1			
SD	230.2				222.3			
CNP-V2	**High Interactivity**				**Low Interactivity**			
	Yes	No	Yes	No	Yes	No	Yes	No
Freq	6	0	11	19	15	1	1	21
%	100%	0%	37%	63%	94%	6%	5%	95%
Latency to Solution								
M	183.2		579.5		404.1		473.0	
SD	137.3		262.8		239.9			

Performance Analysis. To further explore the effects of level of interactivity and order on transfer, a 2-between (increasing interactivity trend, decreasing interactivity trend) × 2-within (CNP-V1, CNP-V2) Mixed ANOVA with CNP performance scored as 0 = never solved, 0.5 = solved one version, 1 = solved both versions was conducted. Considering performance in CNP-V1 only, participants were more likely to achieve insight in a more interactive task environment: $M_{\text{high}} = .42$, $SD = .50$, $M_{\text{low}} = .17$, $SD = .38$, $F(1, 72) = 6.04$, $p = .016$. Across both versions, although participants were more likely to gain insight with a high level of interactivity ($M_{\text{high}} = .45$, $SD = .50$, $M_{\text{low}} = .30$, $SD = .46$), this difference was not significant, $F(1, 72) = .993$, $p = .322$. Insight was more likely to be achieved with the CNP-V2: $M_{\text{CNP-V1}} = .30$, $SD = .46$, $M_{\text{CNP-V2}} = .45$, $SD = .50$, $F(1, 72) = 57.25$, $p < .001$. The improvement in performance across versions varied as a function of the trend of interactivity level, $F(1, 72) = 12.90$, $p = .001$. In other words, improvement in performance from CNP-V1 to CNP-V2 was explained by the trend in interactivity levels experienced. Specifically, when interactivity levels increased (from low to high interactivity), participants had the highest level of improvement. Conversely, when interactivity levels decreased (from high to low interactivity), performance did not improve.

Latencies. For participants who successfully completed both versions of the CNP, latencies to solution were quicker in CNP-V2 than CNP-V1: $M_{\text{CNP-V1}}$ = 575 secs, SD = 219.51, $M_{\text{CNP-V2}}$ = 424.45 sec, SD = 262.94. In a 2 (increasing interactivity, decreasing interactivity) × 2 (CNP-V1, CNP-V2) Mixed ANOVA in which CNP performance was scored as 0 = never solved, 0.5 = solved one version, 1 = solved both versions, the main effect of CNP version was significant, $F(1, 20) = 11.26$, $p = .003$, but the main effect of trend of interactivity level experienced, $F(1, 20) = 2.09$, $p = .164$, and the interaction between CNP version and trend of interactivity level experienced, $F(1, 20) = 3.11$, $p = .093$, were not. In other words, even though the Level of Interactivity did not affect how quickly a solution was found, latencies to solution improved across time as an effect of transfer.

Working Memory Performance

Forward Digit Span. Pooling the data across conditions, participants who solved at least one version of the problem generally had higher FD-Span scores than those who did not solve the problem: M_{Solved} = 11.32, SD = 1.85, $M_{\text{NotSolved}}$ = 10.65, SD = 2.02. However, a regression analysis indicated that participants' performance on the CNP (scored as 0 = never solved, 0.5 = solved one version, 1 = solved both versions) could not predicted by FD-Span, $b = .71$, $SE = .48$, $t(72) = 1.48$, $p = .142$. Therefore, successful completion of the CNP was not explained by participants FD-Span scores.

To explore whether low interactivity burdened working memory, FD-Span scores were compared between those who were completed the low interactivity in CNP-V1 (increasing interactivity trend) and those who completed the low interactivity in CNP-V2 (decreasing interactivity trend). An independent sample t-test showed comparing FD-Span scores indicated no difference between the trend in interactivity level: $M_{\text{decreasing}} = 4.72$, $SD = .50$, $M_{\text{increasing}} = 4.47$, $SD = .50$, $t(72) = .181$, $p = .857$.

Backward Digit Span. The BD-Span scores for participants who solved at least one version of the problem did differ with those who did not solve any version: $M_{\text{Solved}} = 6.47$, $SD = 1.74$, $M_{\text{NotSolved}} = 6.45$, $SD = 1.43$, $b = .02$, $SE = .38$, $t(72) = .056$, $p = .956$.

To explore whether a low interactivity in CNP-V2 burdened working memory, BD-Span performance was compared. An independent sample t-test showed there was no difference between the two conditions: $M_{\text{decreasing}} = 6.61$, $SD = 1.37$, $M_{\text{increasing}} = 6.31$, $SD = 1.77$, $t(72) = .818$, $p = .416$.

Individual Differences Measures

Cognitive Reflectivity. Across both conditions (increasing interactivity trend, decreasing interactivity trend) and performance averaged between versions (0 = never solved, 0.5 = solved one version, 1 = solved both versions), a Pearson's correlation coefficient indicated CNP performance significantly correlated with CRT scores (0 – 3), $r = .311$, $p = .007$. Specifically, higher CRT scores were associated with higher performance average in the CNP. To explore whether the impact of the trend in the level of interactivity experienced was associated with CRT scores, the conditions were assessed separately. When participants started CNP-V1 in the low interactivity condition then CNP-V2 in the high, a positive correlation between CRT and performance average was found, $r = .559$, $p < .001$. However, this was not observed for participants who began with the highly interactive CNP-V1, $r = .138$, $p = .408$. A multiple regression with interactivity trend (-1 = decreasing from high to low, 1 = increasing from low to high) and CRT scores (0 -3) as predictors and overall performance across both versions (0, .50, 1) as the outcome confirmed participants' CRT scores could significantly predict performance in the CNP, $b = .14$, $SE = .05$, $t(72) = 2.78$, $p =$

.001. Further, the effect of CRT scores on CNP performance varied as a function of trend, *b* = .15, *SE* = .07, *t*(72) = 2.21, *p* = .030.

Table 5.6.

Regression Analysis Summary for CRT and Trend Predicting Insight Performance.

Variable	*B*	95% CI	ß	*t*	*p*
		Outcome: CNP Performance			
CRT	0.14	[.024 .24]	0.31	2.78	**.007**
CRT × Trend	0.15	[.14, .28]	0.25	2.21	**.030**

Note. R^2 for Overall Performance = .063

Impulsivity. Across both conditions, a Pearson's correlation coefficient indicated average CNP performance did not correlate with impulsivity, *r* = -.10, *p* = .390. To explore whether impulsivity correlated with performance when data was not pooled, participants' BIS scores were assessed separately based on order of interactivity. Neither starting low (*r* = -.26, *p* = .133) or high (*r* = .01, *p* = .964), correlated with performance. Thus, there was no evidence that impulsivity would be associated with insightful performance in the CNP.

Numeracy. Overall, a Pearson's correlation coefficient indicated average CNP performance did correlate with numeracy, *r* = .24, *p* = .041. Dividing numeracy scores between those who started in the low interactivity condition and those who started in the high interactivity condition, starting in with the low interactivity level correlated with performance, *r* = .35, *p* = .034, but starting high did not, *r* = .174, *p* = .296. In other words, higher numeracy scores were predictive of performance when participants worked first on the low-interactivity version of the CNP-V1.

A multiple regression was conducted with interactivity trend and numeracy scores (0 - 8) as predictors and overall performance across both versions (0, 0.5, 1) as the outcome. The regression confirmed participants' numeracy scores could significantly predict performance in the CNP, *b* = .10, *SE* = .05, *t*(72) = 2.08, *p* = .041. Further, the effect of numeracy scores on CNP performance varied as a function of trend, *b* = .10, *SE* = .05, *t*(72) = 2.20, *p* = .031. This suggests that starting with the high-interactivity version of the CNP-V1 was sufficient to overcome lacunae in numeracy skills.

Table 5.7.

Regression Analysis Summary for Numeracy and Trend Predicting Insight Performance.

Variable	*B*	95% CI	ß	*t*	*p*
		Outcome: CNP Performance			
Numeracy	0.10	[.004 .193]	0.25	2.08	**.041**
Numeracy × Trend	0.10	[.010, .199]	0.24	2.20	**.010**

Note. R^2 for Overall Performance = .057

Maths Anxiety. Overall, a Pearson's correlation coefficient indicated there was a significant negative correlation between CNP performance and the MAS, *r* = -.26, *p* = .018. After separating participants based on order, MAS negatively correlated with performance for those starting low, *r* = -.50, *p* = .002. However, there was no correlation with performance when starting high, *r* = -.184, *p* = .268.

Table 5.8.

Means, Standard Deviations, and Correlations of the Individual Difference Measures.

			Measure			
Cheap Necklace Problem	M	SD	CRT	BIS	NS	MAS
Overall	0.37	0.44	.31**	-.10	.24*	.02*
Low to High	0.30	0.46	.56***	-.26	.35*	-.50**
High to Low	0.45	0.50	.14	.01	.17	-.18

* *p* < .05. ** p < .01. *** p < .001.

Cross-experiment Comparison

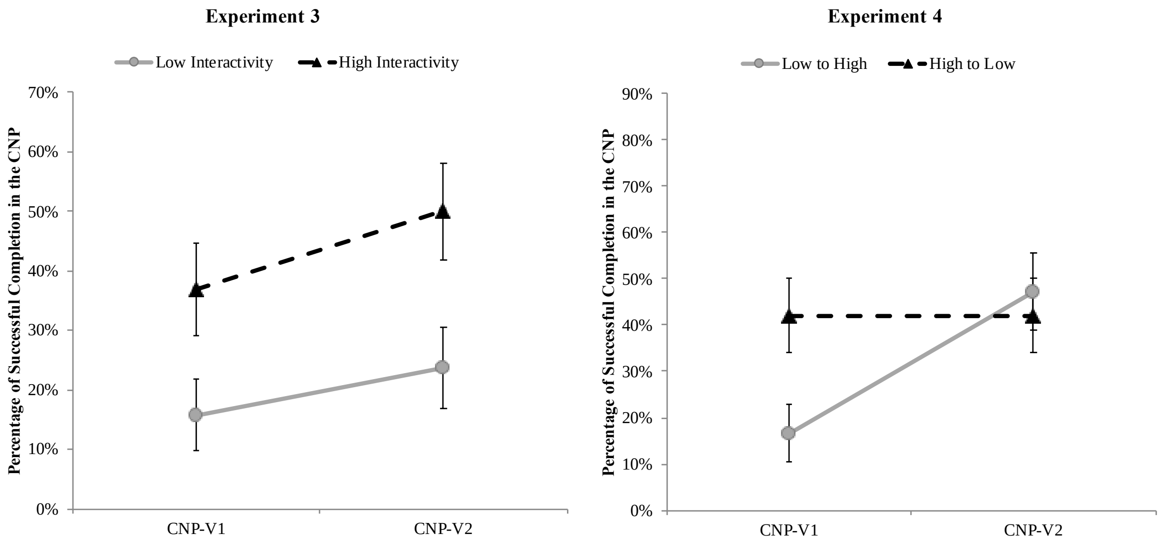

Figure 5.2: Line graphs displaying percentage of successful completion in both versions of the CNP across both experiments.

The data presented in both experiments shows the benefit of a high interactive task environment while attempting either version of the CNP. Further, the switch in the level of interactivity substantially affected performance. This is clearly shown on the basis of a cross experiment comparison. Thus, of the participants who did not solve CNP-V1 in a low interactivity condition in Experiment 3, 4 participants (or 13%) solved the CNP-V2. In Experiment 4, of the participants who did not solve CNP-V1 in a low interactivity condition, 19 (or 63%) were now able to solve CNP-V2 when they were switched to a high interactivity condition, a significant improvement in performance, $\chi^2(1, N = 74) = 4.49$, $p = .034$. Conversely, the switch to a low interactivity condition for participants who started in a high interactivity condition depressed performance considerably. Of the 22 would failed to solve CNP-V1 in Experiment 4 in the high interactivity condition, only 1 (or 5%) solved CNP-V2 in the low interactivity condition. In Experiment 3, of the 24 who failed to solve CNP-V1 in the high interactivity condition, 6 (or 25%) solved CNP-V2. However, this difference is not significant, $\chi^2(1, N = 76) = .477$, $p = .490$. In addition, the difference in solution rate between the high interactivity condition for CNP-V2 in Experiment 3 (37%) and the solution rate in the high interactivity condition for CNP-V1 in Experiment 4 (45%) was not significant, $\chi^2(1, N = 74) = .818$, $p = .366$.

Table 5.9.

Performance improvements in Experiments 3 and 4 following an incubation period (where participants had a break from CNP and completed different tasks), as a function of the initial (CNP-V1) and final (CNP-V2) level of interactivity.

[a] *denotes no change in performance from CNP-V1 high to CNP-V2 low*

	Final interactivity level			
Initial interactivity level	low		high	
	M	*S.E.*	*M*	*S.E.*
low	+9%	0.06	+30%	0.08
high	-[a]	-	+13%	0.08

Discussion

The findings reported in Experiment 4 further support the importance of a high interactive task environment when attempting either version of the CNP. In line with Experiment 3, insight occurred more frequently among naïve participants who were provided with metal chains (high interactivity), compared to those restricted to using just paper-and-pencil (low interactivity). This was also evident in both increasing and decreasing interactivity orders, where all except one participant were able to transfer their solution from CNP-V1 to CNP-V2. Transfer was again shown through participants becoming more efficient in their problem solving: those who found a solution to CNP-V1 were quicker to complete CNP-V2. This was independent of the order of interactivity. In addition, successful completion in CNP-V2 rose substantially, only when the level of interactivity increased. By contrast, decreasing the level of interactivity in CNP-V2 flat lined performance, with just one participant improving across versions.

Exploring the role of working memory, it was found that neither FD-Span nor BD-Span could predict whether people would find a solution to at least one version. Further, the working memory scores did not differ between those who were exposed to an increase in interactivity and those who were exposed to a decrease in interactivity. Therefore, insightful solution to at least one version of the CNP was not supported by a greater working memory span. However, cognitive reflection was again associated with insight (replicating findings from Experiment 3) as well as Numeracy (in contrast to what was found in Experiment 3). Specifically, cognitive reflection scores and numeracy scores of only those participants starting in the low interactivity condition correlated with performance. In other words, when initially attempting the CNP using paper and pencil, the ability to engage in reflective thinking to override an intuitive response as well as the ability to reason with numbers was predictive of insightful performance. This need was reduced when participants completed the CNP in a high interactive environment first.

Performance improved in CNP-V2 only when moving from a low interactive task environment into a high interactivity one. Participants may have struggled to solve the problem when they were restricted to using just paper-and-pencil. Although they didn't produce a solution, it is possible that participants acquired conceptual knowledge about the task requirements. Then high interactive environment in CNP-V2 allowed for these conceptions to be unbridled, leading to subsequent insight. The knowledge gained from CNP-V1 only manifested in the more dynamic task environment. By contrast, starting in a high interactive environment does not limit transfer when the task environment becomes limited, but it does foster new insights in CNP-V2 for participants who failed to solve CNP-V1. More generally, these findings suggest that although transfer occurs regardless of the initial level of interactivity, performance on CNP-V2 with high levels of interactivity is greatly improved, presumably through enactment-driven insight.

General Discussion

The experiments presented in this chapter investigated interactivity and transfer in insight problem solving, using the CNP. To measure transfer, a new variant of the CNP (CNP-V2), which consisted of two four-link chains and two two-link chains was used as a target problem. In Experiment 3, participants attempted the problem with the same level of interactivity as their first attempt (CNP-V1). In Experiment 4, the task environment changed; those who attempted CNP-V1 in a low interactivity condition attempted CNP-V2 in a high interactivity condition, or those who started high went low. As predicted, participants were more insightful in the high interactivity condition, finding the solution significantly more often than those in the low. This was observed in both versions in Experiment 3 and 4. Participants were also able to successfully transfer their solution from the CNP-V1, completing CNP-V2 more quickly. This was observed in both the high and low interactivity conditions, equally when environments offered the same level of interactivity (Experiment 3) and when interactivity levels changed from one problem to the other (Experiment 4). In addition, solution frequencies increased in CNP-V2, thus performance improved across version. However, this improvement in performance was not observed when the level of interactivity decreased (low to high).

Across both versions, interactions with the physical representation of the problems enhanced insight performance. These findings are in line with those in Experiment 1 and 2, and the literature which highlights the importance of interactivity in insight, problem solving and reasoning (Fioratou & Cowley, 2009; Vallée-Tourangeau et al., 2015; Vallée-Tourangeau et al., 2016b). Increased interactivity makes people more likely to find the solution to the source problem but does not increase the likelihood of transfer: The amount of transfer was consistent across interactivity levels in both experiments. Thus, transfer in the present experiments is not explained by the level of interactivity, although performance improvements are.

Insightful solutions occurred more frequently in CNP-V2 than CNP-V1. In Experiment 3, this was observed in both the low interactivity and the high interactivity conditions. However, improvement was only observed in Experiment 4 when the level of interactivity was increased in CNP-V2 (low interactivity to high interactivity). The performance improvements observed follow a similar trend to those of participants attempting the same problem after a break (see Experiment 1 and 2, Chapter 4, p. 97). In Experiment 4, when confronted with a decreasing interactivity level, participants were able to transfer their initial solution to the new problem, but there was no additional improvement of performance in CNP-V2. This is perhaps because the lower level of interactivity removed the possibility of enactment-driven insight, which is physical restructuring. Therefore, insightful performance did not improve.

The performance improvements may be interpreted as CNP-V2 being easier than CNP-V1 rather than an incubation effect. However, Ormerod et al. (2002) determined that the new variant problem is actually more difficult than the original CNP. As the solution to CNP-V2 can be found by joining the ends of two chains together (maximising), initial efforts satisfy participant's criterion for satisfactory progress. Therefore, they can move further in their problem-solving trajectory of constructing longer chains before realising that the solution will require deconstructing one of the chains. If participants have correctly identified that joining the ends of the chain is a costly and incorrect strategy during their attempt their initial efforts, CNP-V2 serves best as a source problem as the detour of breaking the chain into separate links is cost effective. Alternately, allowing participants to do CNP-V2 first, then CNP-V1 can lead to a fixation error. Additionally, Experiment 3 demonstrated a flat-line in solution frequencies across versions when participants had a decreasing interactivity trend.

If CNP-V2 is an easier problem, then at least some performance improvements would be expected. Therefore, the performance improvements observed are better explained as an effect of transfer and incubation instead of the it being an easier problem.

Working memory played a role in insight problem solving, confirmed by the BD-Span working memory scores. Thus, working memory, to some extent, was associated with higher solutions. The scores differed between the low interactivity and high interactivity conditions in the FD-Span and BD-Span. This may be explained as the working memory tests were completed after attempting both the CNP. Efforts to complete the CNP in the low interactivity condition may have burdened subsequent working memory assessments. This, however, did not affect performance on the subsequent high interactive task. In addition, the CRT scores produced some interesting findings. Performance was related to the CRT scores when participants completed the CNP in a low interactivity environment. This may be explained by the fact that most participants began the CNP by joining the ends of two chains together (e.g., Chu et al., 2007), which is an instinctive response when required to join 12 links. However, the CNP is solved by deconstructing a chain into individual links, which is counterintuitive. Therefore, those who scored higher in the CRT may have been advantaged by their higher ability to overcome intuitive responses. However, this positive impact of CRT was not observed in the high interactivity environment. This suggests that the high interactive task environment provided enhanced feedback, allowing participants to overcome the intuition to join the ends of the chain together more effectively than if they performed the task using just paper-and-pencil.

Overall, the findings from Experiments 3 and 4 demonstrate transfer is best when participants can generate their own solution to problems that share sufficient similarity, where nearly every participant transferred their solution to the CNP-V2 having successfully completed CNP-V1. While they could all transfer their solution, an increased level of interactivity was most beneficial as the participants in the high interactivity condition found their solution more often. As such, the findings reported here parallel those of Experiment 1 and 2: While insightful solutions improve across time and version as an incubation effect, insightful solutions are most prevalent when problem-solvers can manipulate tools to create representations of the CNP. Thus, insight is primarily driven through enactment.

Chapter 6: Behavioural Analyses

"We shape our tools and thereafter our tools shape us."

- *McLuhan (1964, p. xxi)*

The experiments reported in the previous two chapters have demonstrated the benefit of interacting with artefacts while encountering difficult insight problems. Specifically, in the Cheap Necklace Problem, interactions with quick-fix metal chains that problem solvers could physically manipulate led to better performance, enhanced the effects of incubation and facilitated transfer. Although the advantage of the high interactive task ecology is clearly shown, it only provides a partial explanation of why this environment is better. Interactive problem solving unfolds in a cognitive trajectory, which shows problem solvers acting and perceiving environmental cues that afford possible actions. Thus, observing problem solvers' interactions enables cognition to be studied through events in which cognitive ecologies produce desired cognitive results (Steffensen et al., 2016). A systemic thinking model approach to insight problem solving offers a theoretical viewpoint on questions that may arise as to the benefit(s) of artefacts, while offering a new methodological avenue to explore this.

Recently, experimental and theoretical papers have argued that tool use augments cognitive resources and offers a scaffold for cognition (e.g.; Guthrie et al., 2015; Guthrie & Vallée-Tourangeau, 2017; Kirsh, 2014; Malafouris, 2015; Vallée-Tourangeau et al., 2016a; Weller et al., 2011). Exactly how and why these interactions matter, however, remains a largely open question (but see Steffensen et al., 2016; Vallée-Tourangeau et al., 2015). To shed light on the importance of these interactions, participants in the experiments presented in this thesis were video recorded, allowing for their actions to be observed, analysed, and scrutinized. Exploring the actions and events foregone by problem solvers in the CNP when interacting with manipulables may show the importance of interactivity. The purpose of this analysis is not to produce conclusive answers, but rather to explore, and draw inferences, from the actions observed to contribute to our understanding of how and why interactivity may contribute to cognition. To begin with, a *first move analysis* was conducted, followed by a *comparative behavioural analysis* as a means to provide a nomothetic explanation of interactive insight problems solving focused on the overall behavioural trends that may have contributed to increased solution rates among high interactivity participants. The first move analysis focuses on the first interactions made by problem solvers, and their impact upon latter insight. The comparative behavioural analysis analyses and compares behaviours undertaken between solvers and non-solvers.

Next, an idiographic explanation will contribute to a more detailed understanding of particular cognitive trajectories, by following a unique individual to account for how a single participant journeyed towards a solution. This is accomplished using the *cognitive event analysis* method (Steffensen, 2013; Steffensen et al., 2016), a qualitative interactivity-based method for studying cognition, and providing detail of how an individual case journeyed towards the correct solution.

Prior research into the CNP has used verbal protocols, where participants were required to verbalize while attempting to solve the problem (e.g., Fleck & Weisberg, 2004; Silveira, 1971) or provide warmth ratings, which are to describe how close participants felt they were to a solution (e.g., Metcalfe & Wiebe, 1987). Although thinking aloud adds depth to understand the problem solvers' thought trajectory, it may be detrimental, as verbalizing is interfering and inhibits insight (Schooler, 1993), and with participants often overoptimistic of their progress (Weisberg, 1992). To prevent any mediating effect of thinking out loud, participants were not required to verbalize; instead, actions and interactions with the chains were video recorded. Video data produce good results in experimental environments where participants can manipulate physical problems (Steffensen et al., 2016).

First Move Analysis

The CNP is a multi-move insight problem, which requires a sequencing of steps in order to insightfully complete the necklace. There is only one correct process to solve the problem, which begins by completely separating a link from its chain. Due to the multi-move process, problem solvers can complete an incorrect sequence through multiple steps believing it will create a solution, yet ultimately lead to a dead-end. The first move in the process of steps is important, as this move may facilitate or hinder insight. In the CNP, the predominant initial move by naïve participants is to join the ends of two chains together (as observed by Chu, Dewald & Chronicle, 2007; Fioratou, 2005; Ormerod et al., 2002). This maximising first move, which creates a 6-link chain, is half of the 12-link necklace, yet only costs a third of the budget, at just 5¢. There is apparent progress towards the goal, yet this move cannot lead to a successful solution because it ends up costing 20¢. Participants have reportedly tried to apply this strategy repeatedly, even when it proves to be unsuccessful (Chu et al., 2007; Chu & MacGregor, 2011). As discussed in Chapter 2, the criterion for satisfactory progresses suggests that if a move meets a benchmark for progress in accordance with the problem statement, solvers with continue through that path (MacGregor, Ormerod & Chronicle, 2001).

The analysis of participants' first moves in the experiments conducted by Chu et al. (2007) did not predict performance but did predict how quickly a solution was found. In the following section, I conduct a similar analysis by reviewing the video evidence of first moves enacted by participants who served in the CNP experiments presented in the previous chapters. The aim of this analysis was to explore (i) whether the first move could predict outcome in the CNP even in the absence of a hint to avoid maximising, (ii) whether the maximising first move is less prevalent among solvers than non-solvers, (iii) whether opening a middle-link first was more common among solvers comparted to non-solvers, and (iv) whether the high interactive task environment facilitates participants' performance by helping them choose the correct first move. Experiment 1 and Experiment 2 allowed participants to use a pen to make notes while attempting the CNP. However, a pen was not provided during Experiment 3 and Experiment 4. As the environment was different and participants had different affordances for the first move, the experiments can be congregated. Observations for E1 and E2 were analysed together and thus referred to as Study 1. Likewise, participants in E3 and E4 were analysed together, referred to as Study 2.

Study 1 (Experiments 1 and 2)

Method

Participants. Forty-two participants from Kingston University consented to be recorded in the high interactive condition (33 females, $M_{age} = 21.35$, $SD = 4.16$). Thirteen participants were recruited in Experiment 1, and 29 participants were recruited in Experiment 2.

Materials. Observations were coded using ChronoViz (Version 2.0.2; Fouse, 2014). One camera was attached to the ceiling above the table participants were working on, and another attached on the wall in front of participants, facing down on the table (see Figure 6.2).

Figure 6.2: Images from video recording of participants at the beginning of the Cheap Necklace Problem. View from camera in front of participants (left) and camera mounted on ceiling (right).

Design and Procedure. A large sample of videos was reviewed to establish a coding criterion of the first moves frequently performed by participants. Based on the actions observed among participants in this study and those reported by Chu et al. (2007), the coding criteria pertained to five domains: aligning two chains, opening an end link, opening a middle link, counting, and writing. Actions were coded as aligning two chains when a participant was observed to place the ends of two chains together, which simulate a 6-link chain, without opening or closing a link. This first move is maximising as it meets the criterion for satisfactory progress. Opening an end link, which is also maximising first move, was opening a link at the end of a chain without removing that link from the chain. Opening a middle link, which is the correct first move sequentially, was coded when participants opened a middle link and isolated it from the chain. First moves were coded as counting when a participant was observed to count the links by pointing at them. Lastly, writing was when participants' initial attempt to complete the CNP was making notes on the problem sheet.

Only participants who consented to be filmed were included in the sample of videos analysed. The video data was collected individually, for each participant and only included first moves in the first experimental session (Time 1)[3]. After participants were provided with instructions, and shown how to open and close the links, the experimenter went to a control room and began filming their hands and the table they worked on.

Results

The results reported below explored the first move of solvers and non-solvers in the Cheap Necklace Problem. The aim of this analysis was to determine whether the first move was predictive of performance in the absence of a hint to avoid maximising (contrary to Chu et al., 2007). A secondary aim was to examine whether the first move of those who successfully completed the CNP predicted how quickly they found the solution.

Cheap Necklace Problem Performance

The first move undertaken by most participants was one of the two maximising first moves; 12 participants (or 28.6%) started by aligning two chains together and 10 (23.8%) began by opening an end link. Of the 12 who aligned two chains together, four (33.3%) successfully completed the CNP, while 5 (or 50%) of participants who opened an end link first found a solution. Ten (or 23.81%) participants began by making the correct first move, opening a middle link, with five of them (50%), ending up finding the correct solution. Five participants (or 11.90%) began by counting. Among those, three (60%) found the solution. The remaining five participants began by writing, none of whom went on to find the solution (see table 6.1).

[3] This study investigated the first moves participants undertook. Behaviours of naïve participants were most important for this analysis, as their first moves are typically unguided and random. Previously attempting the CNP may have tailored behaviours towards what they previously done. In order to unfold the true narrative or participants' first move, only videos from the initial encounter were observed.

Table 6.1.

Frequencies of first moves performed by participants in Study 1 and the corresponding successful completion of the CNP.

	First Move				
	Aligning two chains	**Opening an end link**	**Opening a middle link**	**Counting**	**Writing**
N	12	10	10	5	5
CNP Success	4	5	5	3	0

The first moves of aligning two chains and opening an end link are both satisfy the criterion for satisfactory progress, therefore maximising. In this light, these two categories were combined to determine whether maximising first moves are less prevalent among solvers. Of the 22 participants who began by maximising, nine (or 40.9%) successfully completed the CNP. Eight (or 40%) of the 20 participants who had an alternative first move found the solution, which was not significantly different, $\chi^2(1, N = 42) = .361$, $p = .386$. In other words, starting the CNP by maximising does not make participants less likely to complete the CNP.

To determine if the correct first move, opening a middle-link first, is more common among solvers, solution rates for participants who began by opening the middle link was compared to other first moves. Although those who began by opening a middle link had a 50% chance of successfully completing the CNP compared to 37.5% when starting with a different first move, this difference was not significant, $\chi^2(1, N = 42) = 4.94$, $p = .714$. In other words, starting the CNP by using the correct first move of opening a middle link does not make participants more likely to complete the CNP.

Latencies to Solution

Of the 42 participants in this study, 17 (or 40.48%) successfully found the solution to the CNP. On average, participants took 980 secs (*SD* = 448) to complete the necklace. Those who began by maximising took the longest to find the solution, *M* = 1103 secs (*SD* = 532), while participants who began by opening a middle link found the solution quickest, *M* = 797 secs (*SD* = 322). Those who began by counting took on average 915 secs (*SD* = 328) with no participants who began by writing successfully completing the CNP. Although participants who began differently engaged with the problem for different lengths, the first move did not have an effect on how quickly a solution was found, $F(2, 14) = .762$, $p = .485$.

Study 2 (Experiments 3 and 4)

Method

Participants. Sixty-eight participants from Kingston University consented to be recorded in the high interactive condition (33 females, $M_{age} = 23.95$, $SD = 6.59$). Thirty-four participants were recruited in Experiment 3, and 34 participants were recruited in Experiment 2.

Materials. The same materials used in Study 1 were also used for Study 2.

Design and Procedure. The same design and procedure for Study 1 was also employed for Study 2. However, participants in Study 2 were not provided with a pen and therefore could not write while they were thinking. Thus, only four first moves were coded; aligning two chains, opening an end link, opening a middle link, and counting.

Results

Cheap Necklace Problem Performance

Similar to the findings in Study 1, most participants began by maximizing. Twenty-one (or 30.8%) began by aligning the ends of two chains together, and 10 (47.6%) successfully completed the CNP. Thirty-one participants (45.6%) opened an end link as their first move, with 10 (32.3%) of them completing the problem. Nine (or 13.4%) participants began by opening a middle link, with just three (or 33.3%) finding the correct solution. Four participants (or 7.4%) began by counting, of whom two (or 50%) completing the CNP (see table 6.2).

Table 6.2.

Frequencies of first moves performed by participants in Study 2 and the corresponding successful completion of the CNP.

	First Move			
	Aligning two chains	**Opening an end link**	**Opening a middle link**	**Counting**
N	21	31	9	4
CNP Success	10	10	3	2

To determine whether the most common maximising first moves are less prevalent among solvers, solution rates for participants who began by aligning two chains and opening an end link were compared with those who started with one of the other first move. Of the 52 participants who began by maximising, 20 (or 38.5%) successfully completed the CNP. Eight (or 61.5%) of the 13 participants who had an alternative first move found the solution, which was not significantly different, $\chi^2(1, N = 67) = 1.55$, $p = .295$. In other words, starting the CNP by maximising does not make participants less likely to complete the CNP.

To determine if the correct first move, opening a middle-link first, is more common among solvers, solution rates for participants who began by opening the middle link was compared to other first moves. Those who began by opening a middle link had a 33.3% chance of successfully completing the CNP compared to 42.9% when starting with a different first move. This was not a significant difference, $\chi^2(1, N = 67) = .577$, $p = .589$. In other words, starting the CNP by using the correct first move of opening a middle link does not make participants more likely to complete the CNP.

Latencies to Solution

Of the 68 participants in this study, 27 (or 39.71%) successfully found the solution to the CNP. On average, participants spent 480 secs (*SD* = 220) completing the necklace. Those who began by opening a middle link appeared to spend more time finding the solution, *M* = 760 secs (*SD* = 50), compared to participants who began by joining the ends of the chain, *M* = 443 secs (*SD* = 196), or those who began by counting took on average *M* = 463 secs (*SD* = 327). However, the type of first move enacted by participants did not affect how quickly they completed the CNP, $F(2, 24) = 3.22$, $p = .058$.

Discussion

The first move analysis aimed to explore whether the first move undertaken by participants who were naïve to the CNP could predict their performance when no hint was provided. The analysis further explored whether the maximising first move was less prevalent among solvers than non-solvers, whether opening a middle-link first was more common among solvers compared to non-solvers. In addition, whether the high interactive task environment helps participants start better, by helping them choose the correct first move.

The findings reported in this first move analysis indicate that the first move undertaken by participants is not predictive of overall performance. Most participants began through maximizing, identified by an attempt to make 6-link chain first. The desire to satisfy a progress criterion, which is to adopt what appears to be the most effective first move, was prevalent among most participants. The creation of the 6-link chain, which is half the necklace at just the third of the budget is the most favourable first move. This first move, albeit incorrect, did not hinder participants from eventually finding the solution. In a similar way that the incorrect first move did not hinder participants, the correct first move did not benefit participants. Opening a middle-link, which is the correct first move in the sequence to complete the CNP, may suggest eventual success, yet this was not observed. Whether the first move is outwardly portrayed as correct or incorrect, it did not indicate how a participant will navigate towards a solution. These results are in line with those reported by Chu et al. (2007) where successful completion was not predicted by first move when participants are provided with a hint. In an interactive task, there was no evidence that a maximising first move, was detrimental to performance, contrary to the conclusions by MacGregor et al. (2001) and Ormerod et al. (2002).

Although there were apparent differences in the average time taken to complete the problem based on their first move, these weren't significant. Therefore, the first moves undertaken by participants were not indicative of how quickly they found their solution. Chu et al. (2007, Experiment 2) reported that their participants found the correct solution in fewer trials. Participants in the present study did not find the solution quicker. This difference may be explained by the fact that participants were not provided with a hint. This may have led them to persevere with an incorrect strategy for longer. Thus, in addition to the first move failing to predict performance, the first move was unable to predict latency to solution for successful participants.

Contrary to importance place by MacGregor et al. (2001) and Ormerod et al. (2002), the first move analysis is not a predictor of CNP performance, demonstrated by the findings reported here and Chu et al. (2007). Although a high interactive condition facilitates insightful completion of the CNP, it is not because the artefacts help participants start better. Thus, analysing participants first move is not a good measure of performance and future research might adopt exploring beyond the first move. The difficult nature of the problem is overcoming the incorrect intuition to join the ends of the chains, and to navigate through a seemingly counterproductive route of breaking a chain apart. As shown by the performance rates across the four experiments presented in the previous chapters, most people fail to do so upon their first encounter, even in a high interactive environment. However, it could be suggested that the high interactive environment allows for participants to navigate towards the correct trajectory better, as these participants always outperform those working on a paper-and-pencil version of the task. Thus, it would be valuable to explore the actions and interactions of participants as they attempt to find the solution in an interactive context. With this aim, the next section presents a comparative behavioural analysis comparing the actions of solvers to non-solvers.

Comparative Behavioural Analysis

Observing participants beyond the first move may help better appreciate the processes involved where increased interactivity through tool use facilitates insight. Since first moves are indicative of future successful performance, it may be that path to solution evolves in a longer trajectory. Through methodical observations and a sequential analysis, actions undertaken by problem solvers provide understanding to the way interactivity supports cognition. For example, Vallée-Tourangeau, Abadie, and Vallée-Tourangeau (2015) used interactive versions of Bayesian reasoning problems, which required reasoners to draw statistical inferences from uncertain information using playing cards to represent the possibilities in the problem. In addition to the task ecology, where the increased level of interactivity supported an improvement in statistical reasoning, Vallée-Tourangeau et al. conducted systematic observations of the actions applied to the cards. These analyses revealed that successful reasoners were actively engaged with the reorganisation of the information, by moving the playing cards around and altering the layout they were initially presented with. Those who drew incorrect statistical inferences spent less time engaged in such actions and instead spent more time making small movements that did not alter the layout of the problem. Thus, reasoning was supported through manipulation of the perceptual layout of the problem presentation.

A similar analysis can be undertaken to ascertain the processes involved in a high interactive task ecology that supports participants beyond their first move in the CNP. Through detailed observations of participants' behaviours, it could be determined how much time participants engaged with the chains and to what extent this facilitates insightful performance. The aim of this analysis is to explore the interactions that support insight, while emphasising the qualitative differences between solvers and non-solvers in the CNP. It is predicted, based on the observations by Vallée-Tourangeau at al. that those who successfully complete the CNP spend more time engaging in actions that alter the perceptual layout of the problem than non-solvers. Thus, participants' behaviours were analysed, and time spent engaged in different behaviours measured.

Figure 6.3. Images from video recording of participants engaged in the different behaviour categories: Projection (left), marking (centre) and presentation change (right).

Method

Participants. Sixty-eight participants' videos were analysed, who served in the high interactive conditions upon their first encounter of the CNP in Study 2 (E3 and E4). The decision to use these participants for observation was on the basis after observing a sample of all videos prior, those who participated in Study 1 (E1 and E2) spent much time writing notes, which were not visible on camera. Therefore, only videos where all actions are visible were selected. The 68 participants were categorised as either solvers (n = 26) or non-solvers (n = 42).

Materials. Observations were coded using ChronoViz.

Design and Procedure. In line with a sequential analysis for observational methods, a coding scheme was developed, shadowing Bakeman and Quera (2011). This began by adapting a mutually exclusive and exhaustive coding scheme previously used to conduct a behavioural analysis exploring interactivity. The coding scheme used by Vallée-Tourangeau et al. (2015), as the codes were grounded in distributed cognitive literature and concepts that are important in determining the process in which interactivity augments cognition. Specifically, as these codes were substantiated in the systemic thinking model, the methodological framework used in formation of this CNP. Vallée-Tourangeau et al. (2015) coded participants' behaviour in four types of activity: Projection, Marking, Presentation change, or Epistemic activity (for a full review, see Chapter 3, p. 65).

To begin with, a random sample of videos were watched repeatedly to adjust Vallée-Tourangeau et al. coding scheme, while developing new activities found particularly in the CNP. This was an iterative process of successive refinement resulting in a pilot coding scheme, which was tested against a different sample of videos to identify behaviours that are generic among all observations. This process refined the activities participants were observed to engage in (see Table 6.3): Projection, Marking and Presentation change. Projection, which is the process of creating mental representation of the physical world (Kirsh, 2013; Vallée-Tourangeau et al., 2015). This is different to perception, which is passive awareness of the objects, as projection is actively anchoring mental representations onto the visible world (Hutchins, 2005; Vallée-Tourangeau et al., 2015). It would be feasible to code these observations as Inactivity. Nevertheless, as projection is passive, it is not possible to be certain whether participants were projecting or being inactive (as they both look the same). Thus, observations were coded as Projection when no activity with the chains was observed in line with Vallée-Tourangeau et al. (2015). Interactions with the links or chains that had no major influence in reconfiguration were coded as Marking. Actions that are complementary, such as touching, pointing, or holding a link may support thinking as they guide attention, anchoring perception for exploring the problem (Carlson, Avraamides, Cary, & Strasberg, 2007; Kirsh, 1995). The representation of a problem is viewed as a way of overcoming impasse when attempting to solve an insight problem (Ohlsson, 1992; 2011; Weisberg, 2014). Thus, the final coding category, Presentation change, pertained exclusively to actions that altered the perceptual layout. These actions including picking up or putting down links, moving links substantially, opening or closing links, and creating a different structure with the links (see Figure 6.3). Both the duration participants on average engaged in activity (in seconds) and proportion of time attributed to such activity were coded.

Table 6.3.

Coding scheme used in the Comparative Behavioural Analysis of the Cheap Necklace Problem, including a description and action example.

Coding category	**Description**	**Examples of actions**
Projection	No action with links or chains	Looks at the written problem and/or chains without any action
Marking	Actions with links or chains that have no obvious epistemic or perceptual impact	Moves one or more link(s) slightly (< 2cm) on the table without significantly changing the location; holding one or more link(s) or chain(s); pointing at one or more link(s) or chain(s)
Presentation Change	Actions with links that change that alter the perceptual layout of the problem	Picks up or puts down one or more link(s) from the table; move one or more link(s) or chain(s) significantly (>2cm); open or close a link; rearranges one or more link(s) or chain(s).

To evaluate inter-coder reliability, a research assistant was trained, blind to the outcome of CNP performance, to code videos using the coding scheme developed. Taking both the behaviour category and the sequence of events coded into account with a tolerance window of 1s, the Cohen's κ from a random sample of 18 videos was .80, with a 91.5% average percentage agreement.

Results

Two behavioural measures were analysed: the total duration participants engaged in each behaviour category (in seconds) and the proportion of time (in percentages) they spent engaging in each behaviour category. These behavioural measures were then compared between participants who successfully completed the CNP (solvers), and those who were unable to do so within the allotted 15-minutes (non-solvers).

Duration

The duration participants engaged in each behaviour category was analysed using a 2-between x 3-within mixed analysis of variance. The between-subject factor was successful completion in the CNP (solvers vs. non-solvers) and the within-subject factor was behaviour category (projection, marking, or presentation change). Solvers were observed to spend less time than non-solvers engaged in Projection (M_{solvers} = 70.19, *SD* = 56.12, $M_{\text{non-solvers}}$ = 305, *SD* = 127.80), Marking (M_{solvers} = 65.87, *SD* = 81.26, $M_{\text{non-solvers}}$ = 132.20, *SD* = 90.38) and Presentation change (M_{solvers} = 367.84, *SD* = 181.23, $M_{\text{non-solvers}}$ = 496.07, *SD* 190.69), as shown in Figure 6.4. The Mixed ANOVA revealed there was a main effect in the duration participants engaged in each activity type, $F(2, 132) = 127.48$, $p < .001$, $\eta^2 = .66$. There was also a main effect of successful completion in the CNP, $F(1, 66) = 24.99$, $p < .001$, $\eta^2 = .28$. However, there was no interaction between the two, $F<1$.

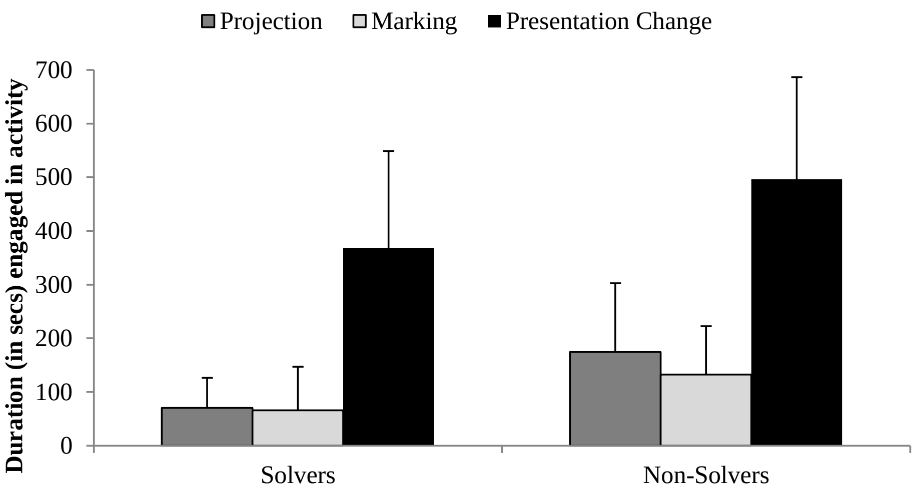

Figure 6.4. A bar graph displaying the average total duration of time (in secs) engaged in each behaviour type.

Proportion

In addition to the duration participants engaged in each behaviour category, the proportion of their total duration was analysed using a 2-between x 3-within mixed analysis of variance. Again, the between-subject factor was insightful performance in the CNP (solvers vs. non-solvers) and the within-subject factor was behaviour category (projection, marking, or presentation change). Solvers attributed a smaller proportion of their time than non-solvers engaged in Projection and Marking behaviours, where solvers spent on average 13.82% of their time Projecting compared to 20.11% for non-solvers and solvers spent 12.80% of their time Marking, compared to 15.83% of solvers. However, solvers spent a larger proportion of their time engaged in Presentation change behaviours (75.65%) compared to non-solvers (64.30%), as shown in Figure 6.5. A Mixed ANOVA revealed there was a main effect in the proportion of time participants engaged in each behaviour category, $F(2, 132) = 230.72$, $p < .001$, $\eta^2 = .78$. There was also a main effect of successful completion in the CNP, $F(1, 66) = 5.00$, $p = .029$, $\eta^2 = .07$. In addition, there was a significant interaction between proportion of time attributed to each behaviour type and successful completion of the CNP, $F(2, 132) = 5.15$, $p =.001$, $\eta^2 = .07$. Post hoc independent *t*-test comparisons confirmed that non-solvers spent significantly more time engaged in Projection than solvers, $t(66) = 2.03$, $p = .047$, Cohen's $d = 0.52$. By contrast, non-solvers spent significantly less time engaged in Presentation change than solvers, $t(66) = -2.70$, $p = .009$, Cohen's $d = 0.69$.

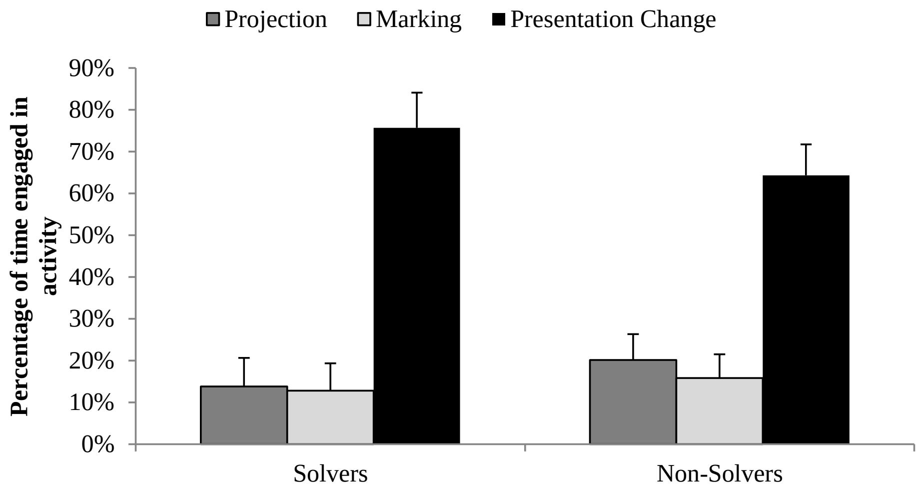

Figure 6.5. A bar displaying the average proportion of time (in percentages) engaged in each behaviour type.

Discussion

The comparative behavioural analysis aimed to explore the interactions that support insight, highlighting differences between solvers and non-solvers in the CNP. It was predicted that solvers would spend more time engaged in actions altering the perceptual layout of the problem than non-solvers in both total duration and proportion of time engaged in each behaviour type. Although there were within subject differences where participants spent most of their total of duration of time engaged in Presentation change behaviours, there were no differences between solvers and non-solvers. In other words, all participants spent most of their time in Presentation change. However, when considering the time spent engaged as a proportion, there were significant and substantial differences between solvers and non-solvers. Specifically, solvers spent a significantly larger proportion of their time allotted to Presentation change behaviours. This conjecture in results between total duration and proportion may be due to solvers typically spending less time attempting the CNP. Once participants successfully completed the task, they stopped. By contrast, non-solvers persisted for the entire 15-minutes. Thus, they spent more time (in seconds) engaged in all activity types, including Presentation change. The analysis on the proportion of time, therefore, may relay more accurate iterations as to the beneficial nature of interactivity in insight. Specifically, gaining insight in a high interactive task environment is benefited by the physical restructuring of the problem presentation. The findings into proportions of time, which were disproportionate within the activity types, differ slightly from the findings reported by Vallée-Tourangeau et al. (2015). In the interactive Bayesian reasoning tasks, participants spent equal proportions of times within behaviour types, which was not observed in this comparative behavioural analysis. However, these findings are line with Vallée-Tourangeau et al. reporting successful reasoners' spending significantly more time changing the layout of the problem. Among both reasoning tasks and insight problems, where a high interactive task environment is afforded, the active engagement in restructuring the layout of the problem is supportive for successful performance. The project-construct-monitor cycle presented by Kirsh (2009) begins to explain this finding. Projection is anchored in external structures, which is enriched awareness and perception (Kirsh, 2010; Menary, 2007). Interactions with the task, constructing new layouts are then monitored. Monitoring whether the construction of the new representation is beneficial to the goal leads back to projection. Altering the representation of the task is key to the cycle, which is beneficial for insight attainment. However, the project-construct-monitor cycle is deductive, in that it assumes one thinks and then projects their mental representations by transforming the environment prior to evaluating the usefulness of those transformations. The systemic thinking model (Vallée-Tourangeau & Vallée-Tourangeau, 2017) would instead suggest that the active engagement in presentation change activity supports insightful performance because it increases the chance for unplanned, serendipitous discoveries. Thus, inductive processing is driven by directly perceived affordances in the world rather than by mental representations and projection.

While attempting to solve the CNP, some participants spend time inactive, not engaged in interactions with the chains. Non-solvers spent a significantly larger proportion of their time than solvers Projecting. While larger proportions of time engaged in interactive behaviours are helpful in completing the CNP, inactivity may be disadvantageous. Evaluating and deliberating permissible moves is helpful when coupled with the interaction and execution of moves. Restructuring the representation of the problem mentally, however, can be cognitively exhausting as it is difficult to have a complete overview of the move trajectory. Spending the largest proportion of time considering moves, not actively making the moves, did not lead to the successful completion of the CNP. This is not to say that Projecting is disadvantageous. Projection and monitoring, albeit physically inactive, are essential components to solving the problem. Rather, spending more time projecting than constructing was unfavourable for the successful completion of the CNP in this study.

The results of the comparative behavioural analysis begin in attempting to explain why interactions with external tools facilitate insight. Specifically, in the CNP, using metal chains that represent the problem, and active engaged in the rearrangement of the task, allowed for a more congenial task environment in which to solve the problem. In the observations presented, participants generally spent most of their time engaged in Presentation change, and least time Marking and Projecting. Interactivity and altering the representation is beneficial but does not guarantee insightful completion of the CNP. It is not clear whether these participants think-then-do, which is change the layout of the problem based on their thoughts. Or whether they do-then-think, which is monitor random changes they've created in attempt to prompt insight. What is clear is that altering the perceptual layout of the problem and spending the largest proportion of allotted time doing is, improves insight performance in the CNP. A single case detailing depiction of a solvers' trajectory may provide useful information for exploring the way in which interactions with chains may lead to insight.

Cognitive Event Analysis

Recognising and categorising common actions undertaken by participants has shown some ways interactivity with external resources facilitates insight. Observing fine-grained interactions enables analyses of events where cognitive ecologies produce desired cognitive results. This section introduces a cognitive event analysis (CEA), a qualitative approach to observing and understanding interactive behaviour. CEA is established in both the distributed cognition system, which explores how agents engage with external artefacts and each another (Hollan, Hutchins, & Kirsh, 2000), and distributed language systems, in which linguists methodically analyse cognitive dynamics that arise in bodily coordination (Cowley & Nash, 2013). The combination of the two systems produces a study of "cognitive ecosystems via a microscopic focus on the bodily and inter-bodily dynamic of gesture, prosody, movements, etc." (Steffensen et al., 2016, p. 82). The analyses are produced through meticulous observations of agents' actions and interactions with their immediate environment, specifically the agent-environment dynamic that alters cognition (Chemero, 2011).

Primarily, a CEA focuses on the identification of five elements; cognitive trajectory, cognitive results, cognitive events, transition points and event pivots (Steffensen, 2013; Steffensen et al., 2016). A cognitive trajectory is the path of continuous actions and transitions directing an agent to his or her desired goal. The cognitive result is the achievement of the desired goal. The cognitive result is often the final occurrence during the cognitive trajectory. This cognitive result, such as gaining insight, is achieved through an aggregate of specific actions occurring along the cognitive trajectory. These can be transition points, which are key moments that help achieve the desired goal, or event pivots, the most prominent transition points. Considering MacGregor et al. (2001) 9-dot problem, the cognitive result is the when the problem solver covers all 9-dots using four continuous lines, reaching the desired goal. The cognitive trajectory is the route taken by the problem solver from the beginning of the problem. This trajectory contains cognitive events, key moments that alter the trajectory; transitional points, such as the realisation that drawing around the parameters of the box won't work, and event pivots, crucial moments such as the realisation that lines can be drawn out of the self-prescribed box. The identification of cognitive events and event pivots are important in understanding the cognitive trajectory. Accordingly, a CEA is centred on events and event identification. The individuals' actions change the environment, allowing him or her to identify the significance of the change. This in turn enables further actions that produce further change (Chemero, 2000; Steffensen et al., 2016).

The CEA has been used in experimental settings to investigate the events that lead to a desired goal. In a river-crossing study with pongos and air cadets, Cowley and Nash (2013) explored the language and the actions in a single case study that rendered it possible for the participant to transport across a river with imposed limitations. Only two parties could fit in the raft, while one party must remain in the raft to row. Pongos must not outnumber air cadets to avoid attack. A CEA focused on how the participant probed for a solution using available resources, namely a physical model of the problem with a raft, pongos and air cadets that can be moved. Steffensen et al. (2016) explored a case study with the 17 Animals insight problem (17A), which required problem solvers to describe how to put 17 animals in 4 equal enclosures in such a way that there are odd numbers of animals in each enclosure. The participant was provided with a pile of pipe cleaners varying in length, 17 zebra figures and written instructions to create the enclosures and place the animals in them. Both Cowley and Nash (2013) and Steffensen et al. (2016) analyses of cognitive trajectories could identify specific cognitive events, transition points and event pivots that produced the desired cognitive result. The identification of these events is essential to understand the agent-environment dynamics that facilitate cognition. Beyond comparing solvers to non-solvers in the river-crossing study and the 17A insight problem, the CEA provided depth and understanding into *how* these problems are solved. The meticulous observations highlight that problem solving is not linear, with solutions being tracked to specific planned or unplanned events. Observing the sense-saturated coordination afforded by the objects in both the river-crossing study and 17A indicates solutions are not always brought about through mental processing. Thus, a CEA observing a single subject using metal chains in the CNP will identify *what* enabled the participant to complete the CNP, and *how* they did so. In this section, observations of a naïve successful solver in the high interactive CNP were analysed. The cognitive trajectory, cognitive results, cognitive events, transition points and event pivots were identified to show how interactivity enabled the participant to gain insight.

Method

Participant. The participant is P127, a 21-year-old right-handed female postgraduate psychology student at Kingston University. P127 who participated in E4, was selected as she successfully completed the CNP in 574 seconds, close to average time of successful solvers in that experiment (*M* = 531 seconds, *SD* = 233). Further, the video offered a clear vision of the participant's actions throughout and the participant consented for the video to be made public.

Materials. Observations were coded and annotated using ChronoViz.

Design and Procedure. This cognitive event analysis followed the systematic observation and analysis process presented by Steffensen et al. (2016), which analysed observations of a single participant solving a difficult insight problem. In line with Steffensen et al. the procedure analysing the video followed five sequential steps: cognitive event identification, event pivot identification, data annotation, cognitive trajectory segmentation and cognitive trajectory analysis (see table 6.4). Cognitive event identification is the identification of key moments along the cognitive trajectory, such as transition points and cognitive results. In the case of the CNP, this can be the isolation of an individual link, making the complete necklace, or additional vital occurrences. Event pivot identification is the pinpointing what provoked the solution. Specifically, the moment that prompted the deconstruction of the chain into individual links. Once these events have been identified, data annotation is next, which is analysing the entire video sequence. In this analysis, the coding process pertained to three domains: participant behaviour, link formation, and chain structure. Participant's behaviour was coded by single activity, sequential actions or individual acts undertaken by the participant. These behaviours were either direct interaction with the links, such as opening a link, or actions not involving the links, such as counting. Link formation was coded as incidents of distributing any of the 12 links, such as moving an individual link or chain around the table. Chain structure refers to changes in the perceptual layout of the chains. The default layout presented was four 3-link chains. The creation of any other type of chain, such as a 6-link, was coded as chain structure. The next step, cognitive trajectory segmentation, is creating a distinct video sequence into defined phases. Lastly, a cognitive trajectory analysis, aimed to answer what enabling conditions for the participants to find the solution, and how the solution was found.

Table 6.4.

The five-steps of a Cognitive Event Analysis with definitions taken from Steffensen et al. (2016, p. 84), including examples of behaviours displayed by P127 in the present CEA

Procedure	Description	Example from the CNP case study
Cognitive event identification	Identification of a cognitive event, typically an organism-initiated change in the layout of affordances in the organism-environment system, in a video record of a naturalistic or experimental data set. The event may be defined from an observer's or a participant's point of view	The behavioral process through which P127 deconstructs a chain into individual links, identifying the links could be used to bridge together the remaining chains
Event pivot identification	Identification of the critical transition point(s) without which the cognitive event would not be this specific kind of event	The instance where an individual link is isolated and this is observed as an affordance for solving the CNP
Data annotation	Segmentation and annotation of (peri-pivotal) idea sequence, using multiple domains and levels, with or without a constrained set of annotation values	Coding and identification of participant behavior, link movement, and chain structure
Cognitive trajectory segmentation	Segmentation of video sequences into *functionally* and/or *behaviorally* defined phases	The nine phases of P127's trajectory: Tryout 1, Impasse 1, Reset 1, Tryout 2, Impasse 2, Reset 2, Tryout 3, Breakthrough, and Verification
Cognitive trajectory analysis	Analysis of how specific segments of the cognitive trajectory (particular the event pivot) are enabled by preceding segment and behavioral tendencies	A miscalculation by P127 when deconstructing a 6-link chain lead to a new formation, leading to an isolated link, may have prepared the solution

Results: A Cognitive Event Analysis in the Cheap Necklace Problem

The single video observing P127 was analysed using the five-step procedure detailed above. Accordingly, the identification of a cognitive event was primary. After identifying the events, annotating the data and detailing a trajectory, this CEA was able to recognize the enabling actions for P127 to find the solution. There are nine phases featuring sequential annotations of observations, including deliberate movements and happenstances during the cognitive trajectory (see table 6.5). The moment P127 gains insight, when she realises the solution requires using individual links to connect the chains, is the breakthrough. The breakthrough is the result of P127's real time actions, whether intentional or not. Accordingly, the trajectory moves backwards away from the breakthrough, to determine if the result was achieved through pre-breakthrough behaviours (Cowley & Nash, 2013; Järvilehto, 2009; Steffensen et al., 2016).

Table 6.5.

The cognitive trajectory of P127.

	Cognitive trajectory	Time	Duration	Definition
1	Tryout 1	-432,400 to -340,500	91,900 ms	Initial attempt; connects the ends of the chains together
2	Impasse 1	-340,500 to -336,700	3,800 ms	Gets stuck; holds head in her hands
3	Reset 1	-336,700 to -257,700	79,000 ms	Starts again; recreated the initial layout of the CNP
4	Tryout 2	-257,700 to -141,500	116,200 ms	Second attempt; tries creative moves
5	Impasse 2	-141,500 to -136,100	5,400 ms	Gets stuck again; stares at chains inactively
6	Reset 2	-136,100 to -59,900	76,200 ms	Recreates initial layout of the CNP
7	Tryout 3	-59,900 to 0	46,900 ms	Third attempt; first move involves isolating a link
8	Breakthrough	0 to 82,800	82,800 ms	Creates the CNP
9	Verification	82,800 to 210,7000	210,700 ms	Retries the solution she created

Observations begin in *try-out 1*, P127 instantly starts to work on the CNP, not taking any time to prepare or read the instructions on the table, which had been previously read to her by the researcher. She begins by connecting the ends of two chains together creating a 6-link chain, which she places down on the table in front of her. She then counts the links in the 6-link chain, indicating that she is calculating how much money she has spent. P127 then picks up the remaining two 3-link chains, and creates a necklace shape on the table, without opening or closing any of links. After a slight pause in action, she joins together the ends of one 3-link chain, which produces a 9-link chain. Immediately, she places her head in her hands, inactively gazing at the chains for 3.8 secs. Without joining the remaining 3-link chain to the 9-link chain, P127 understands joining the ends of the chains will cost too much; she has reached *impasse 1*. P127 quickly *resets* by recreating the original CNP structure directly in front of her. There was no preparation time taken by P127 prior to making her first move. Her actions were deliberate and appeared to be pre-planned. The process in the first attempt was move-pause-move; actions were swift, but were followed by a pondering observed through pauses, then another action. Movement was first, and then the move was assessed. As her previous plan was unsuccessful, P127 spends 7.9 secs looking at the chains after the reset in preparation, passively considering a solution before she executes her next move.

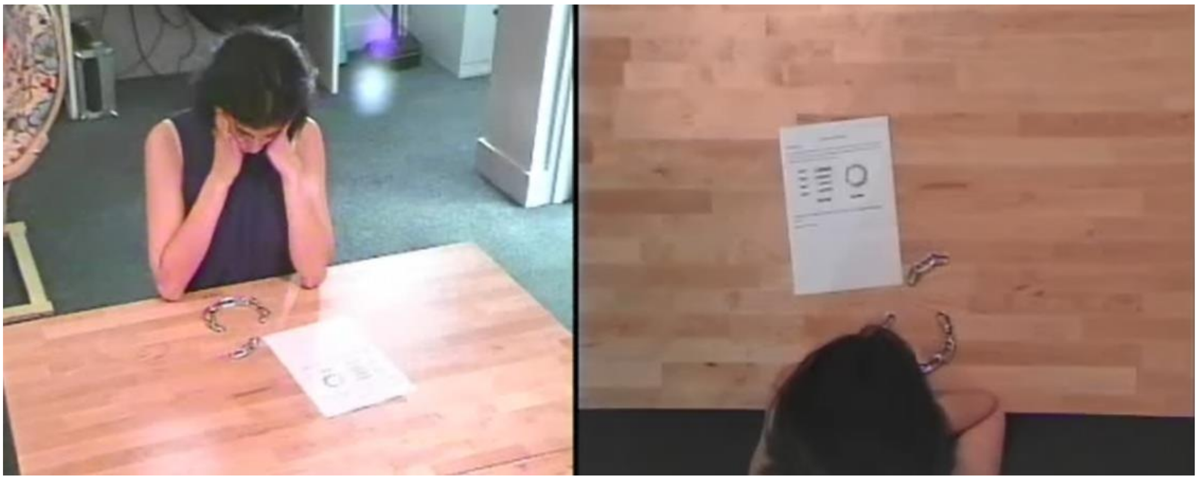

Figure 6.6. P127 reaching the first impasse.

After resetting the problem, *try-out 2* begins with P127 joining the ends of two chains to make a 6-link chain. P127 then places a remaining 3-link chain perpendicular to the 6-link chain without connecting it. As P127 is aware that joining 3-link chain to the end of the 6-link chain will not yield a solution, she sought a creative solution through this reconstruction. However, the reconstruction revolves around the complete 3-link chains, not the constituent links, thus unhelpful. P127 picks up the remaining 3-link chain and holds it in her hand for 4.9 secs while staring at the new formation she'd created. It appears P127 is projecting, looking for a way to fit the chain she is holding into the new formation. After placing the chain back onto the table, P127 abandons the creative solution she was attempting by separating the 6-link chain into two chains. However, instead of separating it into two 3-link chains, she creates one 4-link chain and another 2-link chain. This is an important transition point along P127's cognitive trajectory, as this is the first time the chains are not made of 3-link chains; chains can be deconstructed.

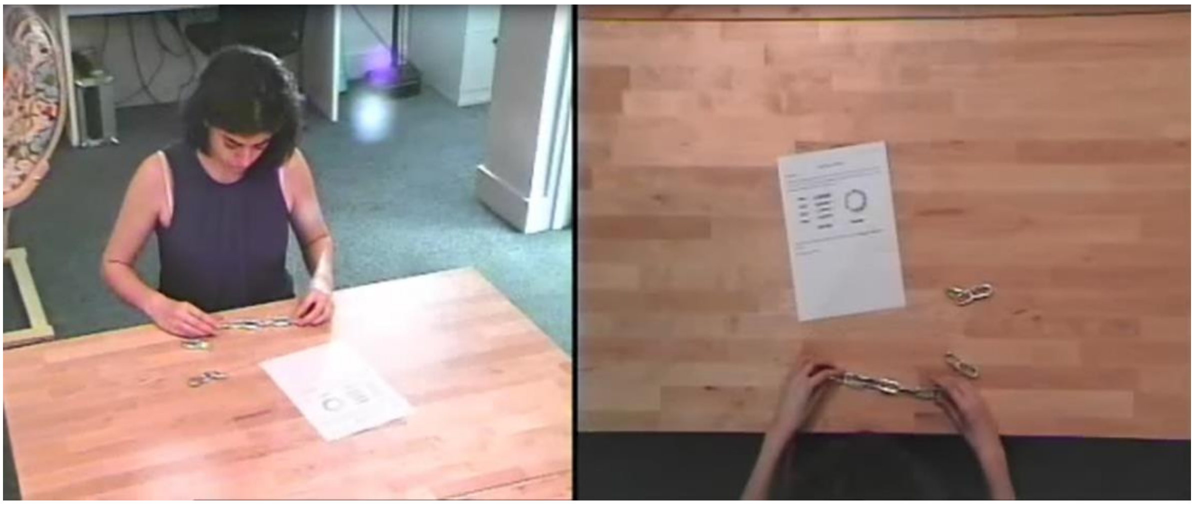

Figure 6.7. A 7-link chain help by P127, a 2-link chain (above P127's right hand) and a 3-link chain.

Neglecting the 2-link chain, P127 creates a 7-link chain from the 4-link chain and a 3-link chain (see Figure 6.7). After placing the 7-link chain straight on the table, she counts the number of links. Once she counts that there are 7-links and not 6-links, she takes a single link off the end of the chain. It seems she was unaware she created a 4-link and a 2-link chain and has rectified her miscalculation and places the single link close to the 2-links. This is another important occurrence for P127, where she has isolated an individual link for the first time through a slip-up when separating a 6-link chain. Although she pays no attention to her action, which is concluded by her grouping the isolated link with the 2-link, this miscalculation was an important occurrence for completing the CNP. Thus, this key event was also identified as a transition point. P127 progresses by adding the 3-link chain to the current 6-link chain directly in front of her. Next, she adds the 2-link chain, creating an 11-link chain, which was positioned in a necklace shape. The remaining isolated link was positioned bridging the ends of the 11-link chain together, although not connected. Placing the single link in between the ends of the 11-link chain was the event pivot that facilitated the solution. The individual link placed in a bridging position is the moment a use for and individual link outside of a chain was created (see Figure 6.8). However, P127 is unaware of this key alteration she has created, reaching *impasse 2*. After staring at the chains inactively for 5.4 secs with her head in her hand she *resets* the problem. P127 spends 5.1 secs looking at the four chains, in preparation for *try-out 3*.

Figure 6.8. The event pivot: P127 has positioned the isolated link (indicated with an arrow) bridging together the ends of the 11-link chain.

P127 began her third attempt by picking up a chain and removing a single link, which was placed back down on the table. She then removes a second link and places it down on the table, leaving her with a single link in her left hand. After opening the link in her hand, she picked up one of the 3-link chain, connecting it with the open link in her left hand. This creates a 4-link chain, with the end link remaining open. With her right hand, P127 then picked up another chain from the table, which she also connects with the open link in her left hand; creating a 7-link chain. She then places this 7-link chain on the table. She counted the links in the 7-link chain, closing the open link that was holding the chain together. She spends 13.9 seconds looking at the chains on the table, assessing the new layout she has in front of her. She moves, pauses to assess the move, and then makes her next move. On the table is a 7-link chain, a 3-link chain and two open individual links. P127 pauses, counts on her fingers, appearing to calculate how much money she has spent prior to resuming activity. P127 picked up one of the remaining two individual links, which was attached to the end of the 7-link chain. She then picked up the 3-link chain, looped into the open link, which was then closes. The formation on the table is an 11-link chain and an individual link. This is the second time she has had this formation, which was observed initially in her second try-out.

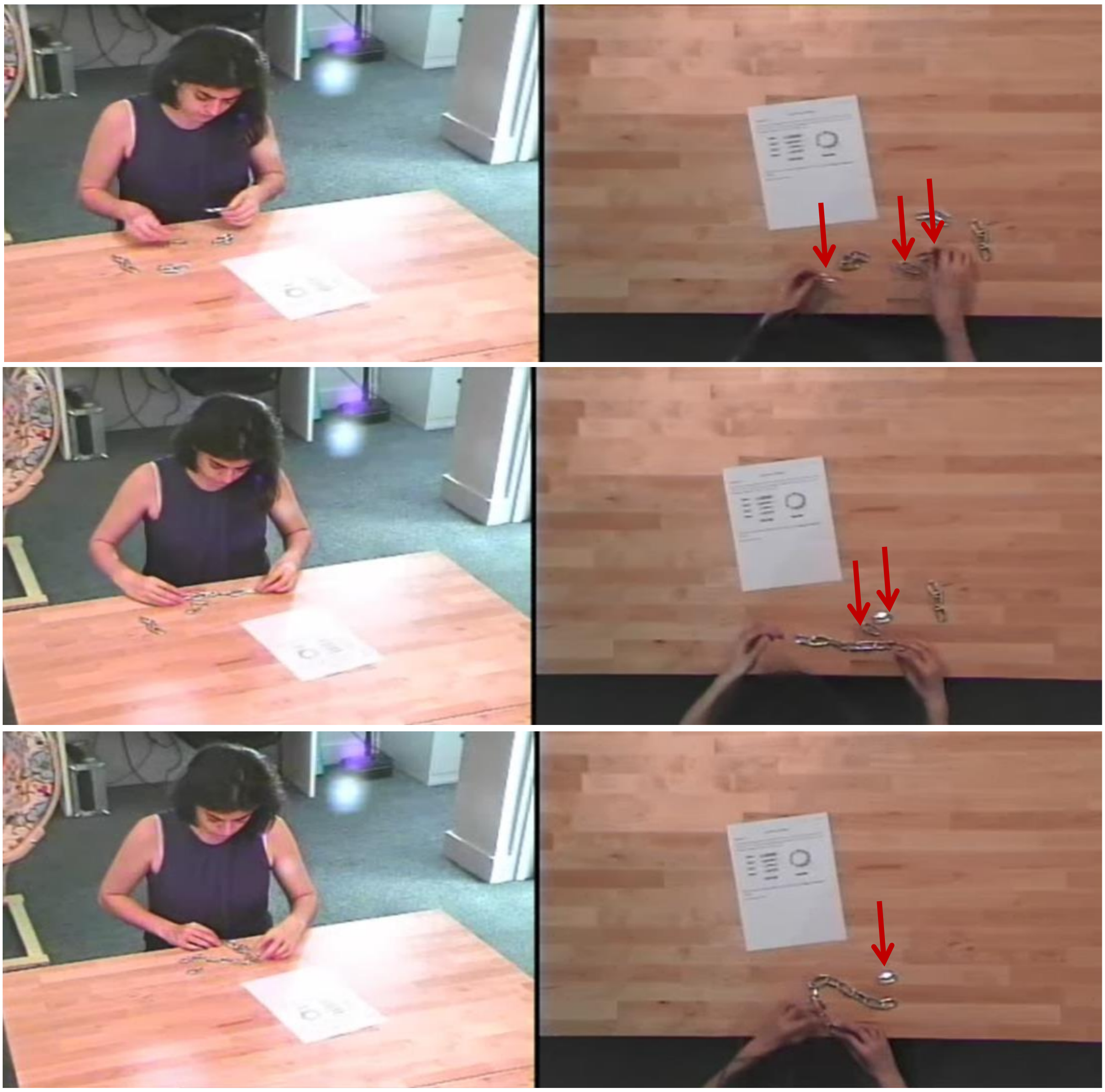

Figure 6.9. The sequence in tryout3. The top image shows P127 isolating three individual links (indicated with arrows). The middle image shows the one link used to join together two chains, leaving two individual links. The bottom image shows P127 recreating the 11-link chain using the individual link in the middle image.

After counting the links in the 11-link chain, P127 immediately picked up the single link to join the two ends of the 11-link chain together. This is the quickest move made throughout try-out 3, appearing to be intentional. It appears P127 has reached the point of *breakthrough*, understanding the purpose and use of the isolated link. After checking all the links are closed, she held the complete necklace up in front of her smiling at her formation. Once P127 achieved the cognitive result of successfully completing the CNP, she verifies that her solution is correct. She resets then recreates the necklace with the exact procedure as try-out 3. Verification, although not necessary, seems to be important for P127, as she spent 210.7 secs recreating the formation again.

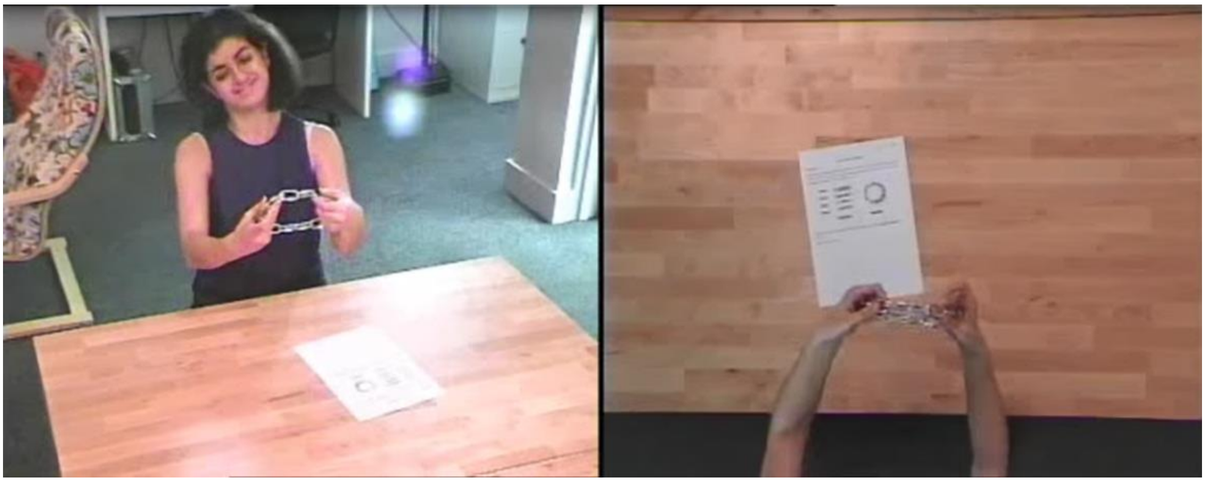

Figure 6.10. Cognitive results: P127 after she successfully completes the Cheap Necklace Problem

The cognitive trajectory, including the identified cognitive events can be visualised in Figure 6.11. Having identified and defined the cognitive trajectory, this CEA will begin to answer *what* enabled P127 to complete the CNP, and *how* did P127 do so. To begin, the activity process of P127, namely "move-pause-move", was examined to answer what enabled her to complete the CNP. Next, the events from the first transition point, namely "miscalculation", until the breakthrough to propose how P127 completed the CNP.

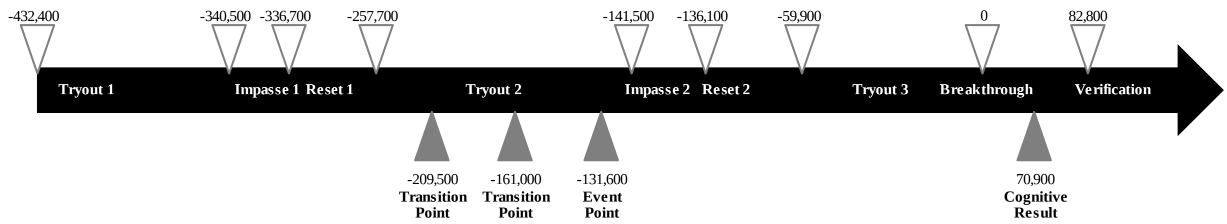

Figure 6.11. The cognitive trajectory of P127, which lasts 574 secs (= 574,000 ms). Unfilled triangles mark phase transitions; filled triangles mark transition points and the event pivot.

Move-Pause-Move

The observed process throughout P127's cognitive trajectory was to move-pause-move; moving then assessing the usefulness of the move. If a move was not deemed to be useful to her, she abandoned the strategy and found an alternative path. P127 did not make a complete necklace prior to successful completion in try-out 3, nor did her moves amount to 15¢. The initial strategy to join the ends of the together was abandoned after creating a 9-link chain. The creation of the 9-link chain cost 10¢, permitting her to open at least one more link (2¢) and close one more link (3¢) before failure, yet P127 abandoned the joining strategy quickly. In her second try-out, the construction of the 6-link chain cost just 5¢. The creative solution of moving a chain perpendicular cost nothing as she didn't attach it. She then abandons this strategy when deconstructing the chain. The process of move-pause-move allowed P127 to identify two things; progress and failure. The alteration in the perceptual layout of the problem, and the assessment of the new layout permitted instant feedback. The metal chains used in this problem are manipulated by the solver to alter the immediate environment. The chains to do not make P127 more insightful, but the activity with the chains alongside her experience with the chains offers dynamic feedback. The feedback informs the subsequent action, which was informed by activity; alterations of the problem through interaction provides opportunity to regulate actions to produce a result (Perry, 2003). The coordination of interaction and information is an integral aspect of cognition (Baber, 2003), thus important for achieving cognitive results. Reconfiguring objects enables examination of current state in relation to the goal state, where progress is monitored through physical rearrangement instead of mental transformation (Kirsh, 2010). By moving, pausing to monitoring progress, and then executing the next move, P127 was able to abandon failing strategies quickly, while incorporating useful moves. The high interactive task ecology provided an optimal environment for this strategy.

Miscalculation

The first cognitive event observed in try-out 2 was when P127 attempted to abandon a failing creative solution. However, in this reset effort, which ought to involve breaking down the 6-link chain into two equal chains, she makes a miscalculation. Instead of breaking down the link equally, she unknowingly creates a 4-link chain and one 2-link chain. Although the intended action was to reset, which can be assumed by subsequent efforts to rectify her mistake, this action was an important event in P127's cognitive trajectory. The miscalculation eventually leads to her breakthrough, therefore a transition point in which a 3-link chain has been deconstructed for the first time. The identification of the individual links that make up the chains is a crucial element in completing the CNP. The new perceptual layout may have cued new possibilities that were not considered where P127 previously made formations consisting of complete 3-link chains. The link formation and chain structure after P127's miscalculation is displayed in table 6.6.

Table 6.6.

The link formation in try-out 2 of P127's cognitive trajectory.

	Link Formation	Action
1	**4**-link chain; **2**-link chain; **3**-link chain; **3**-link chain	Miscalcualtion
2	**7**-link chain; **3**-link chain; **2**-link chain	Joined the 4-link and a 3-link chain
3	**6**-link chain, **3**-link chain; **2**-link chain; **1** -link	Removed a link from the 7-link chain
4	**9**-link chain; **2**-link chain; **1**-link	Joined a 3-link chain to the 6-link chain
5	**11**-link chain; **1**-link	Joined the 2-link chain to the 9-link chain

In order to rectify the miscalculation, P127 removed a link from the 7-link chain she created. This is the second transition point where she has isolated an individual link for the first time. This link isolation, which only occurred due to P127's "error" when deconstructing a 6-link chain, altered the trajectory. Importantly, the isolation of the link was not a deliberate action from pre-existing thoughts on how to restructure the problem. The isolation of a link came about as an unintended consequence of interacting with the chain. Failing to find a use for the isolated link, P127 continues to build the necklace using complete 3-link chains. In the last link formation of try-out 2, the isolated link is placed in a bridging position between the ends of the 11-link chain (see Figure 6.9). This is the pivotal moment, the event when the isolated link has purpose. However, P127 does not use the link, she pauses for 5.4 secs then resets the problem having reached an impasse. The event sequence and the link formation following the event pivot were a direct result of the miscalculation and link isolation observed in try-out 2 (see table 6.7). Aware that an isolated link has a purpose, to bridge together the ends of chains, P127 begins try-out 3 by immediately isolating a link. She is repeating formations that came about through a miscalculation to aid her breakthrough. The case studies into river-crossing and 17A revealed the participants repeated specific actions more than once. However, the repetition of action is not re-doing the same thing as the action is contingent on the participants' perception and understanding of that action. The same action may produce new possibilities, where the action is repeated, yet the thinking attributed to the action is different. Thus, these are "repetitions without repetitions" (Cowley & Nash, 2013, p. 195). The isolation of a link more than once appears to be a repetition; however, the intention behind the isolation is crucial. The first isolation was to rectify an error; the second isolation was producing a necklace, which is a repetition of an action without a repetition of intention. The breakthrough moment was when the repeated bridging of the 11-link chain originally observed in try-out 2, was considered as useful. There was a repetition of a formation without a repetition of the intention of the formation.

Table 6.7.

The link formation in try-out 3 of P127's cognitive trajectory.

	Link Formation	Action
1	**3**-link chain; **3**-link chain; **3**-link chain; **3**-link chain	Default formation of the CNP
2	**1**-link; **2**-link chain; **3**-link chain; **3**-link chain; **3**-link chain	Isolates a single link froma 3-link chain
3	**1**-link; **1**-link; **1**-link; **3**-link chain; **3**-link chain; **3**-link chain	Deconstructs an entire chain into 3 links
4	**4**-link chain; **1**-link; **1**-link; **3**-link chain; **3**-link chain	Adds single link to a 3-link chain
5	**7**-link chain; **1**-link; **1**-link; **3**-link chain	Adds a 3 -link chain to the 4-link chain
6	**8**-link chain; **1**-link; **3**-link chain	Adds a single link to the 7-link chain
7	**11**-link chain; **1**-link	Adds the 3-link chain to the 8-link chain
8	**12**-link chain complete	Uses the single link to connect the ends of the 11-link chain

Discussion

The cognitive event analysis of P127's journey from problem presentation to insight explored what enabled P127 to complete the CNP, and how P127 did so. The analysis revealed that rectifying a miscalculation eventually lead to the isolation of a single link. This link isolation is rudimentary for completing the CNP yet came about as an unintended consequence of P127's interactions with the physical model. The way in which the link isolation transpired for P127 draws attention to the multiple ways insight may occur in the CNP. In the case of P127, insight was traced back to an accident, a simple miscalculation. Should a CEA be conducted on another successful participant, it is possible insight may be traced to a single link falling onto the table during constructions, or even a culmination of random formations. The CNP lends itself to a rich diversity of inadequate attempts; accordingly, many alternative trajectories may be observed (Silveira, 1971). Altering the perceptual layout of the problem through pre-mediated moves, serendipity, or chaos, is beneficial for overcoming an impasse. As observed in the comparative behavioural analysis presented in the earlier section of this chapter, physically restructuring the problem is better than remaining inactive. Thus, the amount of time P127 spent engaging in the reformation of the CNP presentation expedited breaking an impasse.

The basic internalist view of overcoming an impasse is through a ‘special-process’ of thinking, where insight is an unconscious experience with sudden awareness for the solution (Fleck & Weisberg, 2004, 2013; Ohlsson, 1992, 2001; Perkins, 2000), a ‘business-as-usual’ sequential processing of pre-existing knowledge (Bowden, Jung-Beeman, Fleck, & Kounios, 2005), or an integration of the two (Weisberg, 2014). The views on insight attainment place large demand on the problem solver’s cognitive load (Ohlsson, 1992, 2011; Weisberg, 2014), and neglect the agent-environment dynamic (Chemero, 2011). This important interchange between the solver’s knowledge and the tools allows for holistic non-linear observation of the complexity into how insight is achieved (Wilson & Clark, 2009). In the case of the present CEA, it is not possible to remark whether the breakthrough came about through the ‘special-process’ or was ‘business-as-usual’. It is possible, however, to conclude that through interactions and miscalculations, P127 was able to successfully complete the CNP. A seemingly unimportant event (the deconstruction of a 6-link chain) had important consequences. However, accidently creating a chain with fewer than 3-links, resulting in an isolated link did not bring forth the breakthrough. Understanding the purpose and use of the isolated link was the moment of breakthrough. The reflective ability for P127 to keep useful changes and abandon unproductive strategies was crucial for attaining insight. The physicality of the problem alone cannot account for the breakthrough, rather, the dynamic exchange between action and perception between the solver and the environment. Wrapped in the interactions with the chains, where physical changes in the task anchored her attention, P127 was able to complete the CNP.

General Discussion

The present chapter sought to explore participants' interactions with the metal chains when solving the CNP to understand how and why interactivity augments insight performance. The behavioural analyses began by exploring whether the "correct" first move, of opening isolating an individual link, was more prevalent for those who found the solution. The initial move was considered to have some impact on overall performance in the CNP, where an incorrect move may hinder progress (e.g., Macgregor et al., 2001; Ormerod et al., 2002), while a correct first move may generate a quicker solution (e.g., Chu et al., 2007). None the less, participants may have taken a literal understanding as to what it means to "join all 12-links into a single circle" by immediately joining together the ends of the links. It may be for this reason the first move was not indicative of insightful performance. The strategy of joining the ends of the chains together is to a certain extent intuitive. Although this move lends itself to the criterion for satisfactory progress, it may not be maximising, but simply following instructions. The first move analysis could not report significant findings as the first move may have had little to do with the task environment, and more do with the cumbersome instructions to "join". This is not to dismiss the analysis of first moves, rather, to question whether a later move should be determined as the first move. The early investigation into the CNP by Silveira (1971) allowed participants to begin the problem after problem realisation, when participants understand what the task is actually requiring of them. Permitting participants to begin the problem after problem realisation, where they are aware that joining won't work may generate a richer starting point in which to investigate a first move. Silveira's (1971) verbal protocols, which began after problem realisation, provided the opportunity to investigate the solution process in detail, including the starting point. Participants in the present study were not required to think aloud as this may have inhibited insight. It is therefore problematic to determine when, and even if, problem realisation occurred for all participants. Consequently, the first move analysis in the present study is in fact an analysis into the first encounter of the CNP.

As there was no evidence of the first move affecting CNP performance, continuing to analyse the pathways undertaken by participants, a comparative behavioural analysis explored the entire solution trajectory, comparing the interactions of successful and unsuccessful problem solvers. This analysis showed that the key to successfully completing the CNP is spending the largest proportion of time altering the perceptual layout of the problem presentation. By contrast, a lack of interactivity the problem elements (i.e. projection) hinders solution. To expand on these findings further, a cognitive event analysis, which focused on the solution trajectory of just one participant found unplanned, unguided, serendipitous moments can lead to insightful solutions.

Insight and interactivity are personal experiences. The findings from these behavioural analyses provide some objective explanations indicative of patterns emerging when insight was achieved through interactivity, in addition to a fine-grained analysis of the subjective experience of a single participant. Altogether, the qualitative findings presented help us begin to understand that artefacts are beneficial when we interact with them. The presences of the chains alone did not facilitate insight; it was the constructions and reconstructions, which allow for dynamic explorations and feedback. As McLuhan (1964, p. xxi) states, “we shape our tools and thereafter our tools shape us.” Regardless of the first move made, those who took advantage of the malleability of the objects through spending the largest proportion of their time reconfiguring the task environment were most likely to complete the CNP. These findings supplement the quantitative data reported in the previous chapters, capturing behaviours and phenomena imperceptible in frequencies and performance analyses. While adding to the discussion of agent-environment interactions, this only begins to scratch the surface on potential methodologies that can further explore how and why interactivity scaffolds insight.

Chapter 7: General Discussion

"It is the mind-body-scaffolding problem. It is the problem of understanding how human thought and reasoning is born out of looping interactions between material brains, material bodies, and complex cultural and technological environments. We create these supportive environments, but they create us too."

- *Clark (2003, p. 11)*

The 'Aha!' experience has historically been explained through an internal cognitive framework, in terms of restructuring mental representations (Baddeley, 2012; Newell et al., 1972; Maier, 1930). However, external actions also facilitate insight. When presented with a physical representation of a task, making changes to the physical representation, even arbitrary, offers cues to new strategies, enables better planning and efficiency in progressing towards a goal (Steffensen et al., 2016). Accordingly, when problem solvers can interact and restructure their environment, their abilities to solve insight problems are enhanced (e.g., Fioratou & Cowley, 2009; Vallée-Tourangeau et al., 2016b; Weller et al., 2011). Insight problems are also typically made easier when problem solvers take a break from their solution attempts, namely through an incubation period (Segal, 2004; Sio & Ormerod, 2009). Similarly, transferring previously learnt information to a new problem also facilitates insightful solutions (Chen, 2000; Gick & Holyoak, 1980; 1983; Knoblich et al., 1999). On this basis, the programme of research in this thesis was to explore insight beyond just internal cognitive processes, incorporating external actions to enhance insightful solutions. Four experiments investigated interactivity in insight problem solving using the Cheap Necklace Problem. The task environment was organised by varying the level of interactivity offered. Further, the experiments sought to explore the effect of varying the level of interactivity on both incubation and transfer. Observing problem solvers' interactions enabled the exploration of how and why altering the task ecologies produce desired cognitive results. The findings from the experiments led to support the conclusion that cognition draws on systemic resources to emerge, and insightful solutions are often enactment-driven.

Overview of Experimental Manipulations and Behavioural Analyses

Informed by the systemic thinking model (Vallée-Tourangeau et al., 2015; Vallée-Tourangeau & Vallée-Tourangeau, 2017), across the four experiments, the Cheap Necklace Problem (CNP) was presented in either a low interactivity or high interactivity condition. In the low interactivity conditions, problem solvers attempted a paper-and-pencil version of the CNP using a pencil to makes notes. In the high interactivity conditions, a set of four metal chains representing the problem, which could be opened and closed were used to physically construct a solution. In addition, video-based observations of high interactivity participants offered a detailed quantitative and qualitative analysis of interactions during the problem-solving trajectory.

Experiments 1 and 2

Experiments 1 and 2 presented in Chapter 4 investigated whether an incubation effect is influenced by the level of interactivity afforded. Incubation was explored by placing a two-week delay between an initial attempt of working on the problem and subsequent efforts. In Experiment 1, participants reattempted the CNP with the same level of interactivity as in their initial encounter. That is, if problem solvers were in a low interactivity condition during their initial attempt (Time 1), they reattempted the CNP in a low interactivity condition again after the two-week incubation period (Time 2). Likewise, those who initially attempted the CNP in a high interactivity condition later returned to a high interactivity version of the problem. In Experiment 2, participants reattempted the task with a different scope of action possibilities; they switched from low interactivity to high interactivity or high interactivity to low interactivity. It was expected that those in the high interactivity condition would produce insightful solutions more frequently than those in the low interactivity environment. Insightful solutions were also expected to be found most frequently following the incubation period. It was further predicted that the incubation effect would distinctly vary as a function of the level of interactivity.

Experiments 3 and 4

The effect of transfer and interactivity was explored in Experiments 3 and 4 using two versions of the CNP. The new variant (CNP-V2, adapted from Fioratou 2005), consisted of two 4-link chains and two 2-link chains. Both versions require breaking one smaller chain into individual links, then using those links to create a complete necklace. Participants started by working on the standard version (CNP-V1, the source problem) of the problem, then following a break, worked on the new variant (CNP-V2, the target problem). Participants in Experiment 3 remained with the same level of interactivity for both versions of the CNP. In Experiment 4, participants had the task environment switched from low interactivity to high interactivity or from high interactivity to low interactivity, altering the scope of action possibilities. It was expected that those in the high interactivity condition would produce insightful solutions more frequently than those in the low interactivity environment. Successful transfer was also expected to be observed, with participants being able to produce insightful solutions for CNP-V2. It was further predicted that the rate of transfer would distinctly vary as a function of the level of interactivity.

Behavioural Analyses

In Chapter 6, a qualitative approach was undertaken to greater understand how and why interactivity matters. A selection of participants was video recorded in order to analyse and explore the trajectories undertaken while navigating towards completing the CNP. The first move has often been considered to impact on insightful performance, where an incorrect move may hinder progress (Macgregor et al., 2001; Ormerod et al., 2002), while a correct first move may lead to insightful solutions more often and more quickly (Chu et al., 2007). To explore the role the first move had on insight performance, the behavioural analyses began with a first move analysis, which examined the potential differences in the way solvers and non-solvers started the problem. This was followed by a comparative behavioural analysis (Vallée-Tourangeau et al., 2015) of participants' interactions with the metal chains throughout their attempt of the CNP. The actions and interactions of solvers and non-solvers was compared to examine why interactivity helps some participants reach the insightful solution but not others. Lastly, a cognitive event analysis (CEA, Steffensen et al., 2016) meticulously analysed the entire trajectory of a single solver identifying the specific events that made it possible for her to successfully complete the CNP.

Overview of Contribution to Knowledge

Incubation

Insightful performance following a break in active engagement on the CNP improved both in terms of solution frequencies and latencies. The lowest observed performance in Experiment 1 was when participants attempted the CNP in the low interactivity, paper-and-pencil, environment at both Time 1 and Time 2. Even in this most challenging task environment, a break in active engagement promoted insight. There are two possible explanations for this; participants cheated by searching for the solution during the two-week time break, or performance improved due to an incubation effect. The two-week incubation period was more representative of the type of incubation that is often reported in anecdotal accounts of incubation (e.g., Henri Poincaré took breaks of weeks or month before mathematical theorems came about). Although participants were instructed not to think of the problem during the two-weeks, it is not possible to control their activity in that time. Nevertheless, it is unlikely they cheated as performance improvements varied as a function of the level of interactivity. Experiment 2 demonstrated the high interactivity level played a critical role in improving insightful solutions at Time 2: Participants who started in the high interactivity condition and were later limited by low interactivity, did not improve. Assuming that the propensity to cheat was the same in all experiments, one would expect that performance would improve in all conditions in both experiments if cheating took place. As such, it is most plausible to attribute the observed improvements in performance to an incubation effect.

In Experiments 3 and 4, performance increased between the two CNP versions. Albeit not the aim of those experiments, it is conceivable that the improvements in performance from CNP-V1 to CNP-V2 were also served by an incubation effect. The solution rates were substantially higher for CNP-V2, excluding when participants moved from a high interactivity condition to a low interactivity condition (where performance remained the same throughout). It is possible that an incubation effect manifested itself while participants completed the cognitive reflection test (CRT) and the Barratt's impulsivity scale (BIS), which presumably diverted their attention away from the insight problem. In line with Experiments 1 and 2, the incubation effect was contingent on the level of interactivity; remaining with the same level of interactivity or increasing interactivity was most beneficial. However, reducing the level of interactivity (high interactivity to low interactivity) did not enable improvements in performance. Participants in Experiments 3 and 4 were not permitted to leave the lab during their trials, therefore not given the opportunity to cheat by searching for the correct solution. Nevertheless, these results parallel those in Experiment 1 and 2.

Problem solvers need to search their memory or environment for specific strategies, in which an incubation period facilitates knowledge activation and problem restructuring (Sio & Ormerod, 2009). Some researchers assert the performance improvements following an incubation period are due to problem solvers continued conscious-work on a task, with the break allowing room for complementary problem-solving activity (Gilhooly, 2015). Mistaken assumptions relating to the problem are weakened and forgotten, leading to renewed efforts when the problem is later resumed (Smith, 1995). Accordingly, when reattempting the problem after an incubation period, a more effective strategy can be implemented. Similarly, withdrawing attention from a problem allows for the removal of misleading assumptions to enable more useful ones (MacGregor et al., 2001) and mental representations of the problem are restructured more amenably (Seifert et al., 1995). Others have proposed insightful solutions following an incubation period may emerge through unconscious processes a problem solver is ignorant to (Gilhooly, 2016; Sio & Ormerod, 2009). As it was not possible to control the types of activities the participants engaged in during the incubation period, it is not feasible to determine whether the solutions at Time 2 were facilitated by continued conscious-work or unconscious processes. If an incubation effect is partly driven by adopting a fresh perspective of the problem and relaxing self-imposed constraints (Fioratou et al., 2010; MacGregor et al., 2001; Ormerod et al., 2006), individuals' long-term memory would be implicated in insightful solutions. Long-term memory scores in Experiments 1 and 2, measured by the decline from Time 1 to Time 2 in the number of distinct ideas recalled from a short description of the Sun at Time 1, were slightly higher for participants who only found the solution at Time 2. However, there were no meaningful differences in long-term memory scores across conditions or time. In other words, improvements in performance were not explained by problem solvers being able to remember, or beneficially forget.

The two-week incubation period yielded at least the same benefits of the short incubation often observed in scientifically controlled laboratory studies, which often last just a couple of minutes (e.g., Gilhooly et al., 2013). The break in active engagement may have allowed solvers to begin at Time 2 or CNP-V2 attending to more suitable solution attempts. Following incubation, the problem-solving path was more goal directed, which would explain the observed improvements in performance. Accordingly, the incubation effect observed in these experiments was enactment-driven: The incubation effect was most manifest when problem solvers experience a high level of interactivity at Time 2 or CNP-V2 in which they could physically construct their solution. In other words, people who start in a low interactivity environment perform somewhat better in the same environment on the second trial, but a lot better if they switch to a highly interactive environment at that point. Starting in a high interactive environment facilitates insight but ending in a high interactive environment facilitates insight and incubation. This finding suggests that restructuring following an impasse is not completely housed in mental representations. Interactivity matters: The ability to extend mental representations through cognitive interactivity enhanced insights beyond incubation effects alone.

Transfer

In Experiments 3 and 4, participants who found a solution to CNP-V1 successfully transferred their solution to CNP-V2 without any hint or feedback on performance. Transfer was also demonstrated by participants becoming more efficient in their problem solving: those who found a solution to CNP-V1 were quicker to complete CNP-V2. Although insightful solutions were more frequent among high interactivity participants for CNP-V1 (i.e., they were more likely to find the solution than the low interactivity participants), transfer was equivalent to those in the low interactivity condition. Spontaneous transfer, which is transferring a solution in the absence of a hint to use previous acquired knowledge, is seldom observed (e.g., Gick & Holyoak, 1980; Fioratou, 2005). The participants in the Experiments 3 and 4 were required to generate a solution for CNP-V1 themselves, without any feedback on their performance before engaging with the next problem. Without a hint to use a similar strategy to CNP-V1, those who successfully found a solution were able to successfully transfer and find the solution for CNP-V2. Participants were not just re-solving a problem they'd already solved. While it may seem obvious that the solution to CNP-V2 also requires the deconstruction of a complete link, based on the previous solution, this strategy would not be very helpful in CNP-V2. The solution requires that participants connect the ends of the two 4-link chains and use two individual links to connect the remaining chain. The solution to CNP-V1, however, teaches participants that joining the ends of any two chains is wrong. In other words, the solution to the target problem requires problem solvers to ignore the most frequent error they've learnt to correct. Without a hint or feedback on CNP-V1 performance, transfer was readily achieved.

The similarities in the two versions of the CNP, which were apparent, sharing structure and similar procedure to complete, aided transfer. Moreover, not providing a hint, or even feedback on performance after completing CNP-V1, did not limit transfer (contrary to Fioratou, 2005). These findings highlight the importance of similarity for successful transfer, especially in the absence of a hint. However, similarities alone are not sufficient for explaining the large transfer effect. These findings may be explained by the difficulty of the problem. In the matchstick algebra experiments, Knoblich et al. (1999) found that solving the most difficult matchstick problem first, later resulted in highest transfer rates. Similarly, performance in the present experiments show that encountering the difficult CNP-V1 resulted in large amounts of transfer in CNP-V2, as well as problem solvers becoming more efficient as measured by their quicker latencies to solution.

Fioratou (2005, Experiment 9) reported participants were not able to transfer their solution from the target problem to the source problem. They were able to recreate a structure they created but failed to learn the concepts required for forming new, yet similar solutions. The identically similar and difficult CNP versions Fioratou used were used in Experiments 3 and 4. However, the results display two different stories. Aside from two participants in Experiment 4, all other participants were able to use both procedural and conceptual knowledge they obtained from CNP-V1 to help find the solution to CNP-V2, which was not observed by Fioratou. The difference can be explained by a key methodological difference; Fioratou provided the solution to the source problem to all participants (those who found the solution and those who didn't) before they attempted the target problem, participants in Experiments 3 and 4 were not. As Dreistadt (1969, p. 172) explains "when a person discovers something new he is not learning what is shown to him; he is learning something new *as he discovers it*". When a solution to a source problem is self-generated (i.e., discovered, not provided), participants are actively engaged and themselves learn to avoid simply joining the ends of the chains. When faced with the target problem, they are able to ignore the most frequent error they've learnt to correct. This suggests that self-generated solutions to source problems, especially when the problem is difficult, can promote transfer. In other words, successfully completing CNP-V1 was a key driver for insightful solutions for CNP-V2, regardless of the interactivity level. Nevertheless, interactivity matters: a highly interactive task environment doesn't make you more likely to transfer your solution across, but it makes you more likely to solve the first task, and that is key to enable transfer.

Interactivity

As expected, across the experiments, naïve participants in the high interactivity condition produced the correct insightful solution more frequently than those in the low interactivity condition. These findings are consistent with others showing that increasing affordances (i.e., possibilities to physically process the elements of the task) facilitates problem solving (Guthrie, et al., 2015; Guthrie & Vallée-Tourangeau, 2015; Fioratou & Cowley, 2009; Steffensen et al., 2016; Vallée-Tourangeau et al., 2015; Vallée-Tourangeau et al., 2016b; Weller et al., 2011).

Working memory has often been associated with insightful performance in problem solving (Chuderski, 2014). However, the evidence is mixed (DeCaro, Van Stockum, &

Wieth, 2016). Larger executive functions (i.e., being able to do more “in your head” at the same time) are beneficial for solving insight problems. The process of restructuring the problem to break the impasse relies on a large cognitive load (Ohlsson, 2011). Previous work exploring problem solving found working memory was not associated with insight problems in highly interactive task environments (Vallée-Tourangeau et al., 2016a). The C-Span scores from Experiments 1 and 2 suggested working memory was in part able to explain insightful solutions; C-Span scores were generally higher for those who successfully completed the CNP. In Experiments 1, C-Span scores moderated solutions for low interactivity conditions, but this effect was dampened in the high interactivity: Those who attempted the CNP in a high interactivity condition both times had higher C-Span scores. This was not observed in Experiment 2 when participants experienced both levels of interactivity. In Experiments 3 and 4, participants working memory was measured by scores on the forward digit span (FD-Span) and backward digit span (BD-Span) working memory tests. Although FD-Span was not associated with insightful solutions, BD-Span scores were higher in those who successfully completed the CNP. Further, BD-Span scores were lower for participants who attempted at least one version the CNP in low interactivity conditions. This effect diminished for those in the high interactivity condition.

The difference in working memory scores between participants in the low interactivity condition and those in the high interactivity condition could be due to the fact that participants were tested *after* they attempted the CNP. Efforts to complete the CNP in the low interactivity condition may have had a detrimental impact on subsequent working memory assessments (Schmeichel, 2007). This suggests that the initial effort to solve the initial CNP in a low interactivity environment was taxing in executive control, later undermining the participants’ ability to successfully complete the working memory test. Moreover, the fact that this finding disappeared when participants encountered the CNP in a high interactive environment twice suggests that solving the CNP task in such an environment is less taxing in executive control (in line with Vallée-Tourangeau et al., 2016a). In Experiment 4 when the interactive condition was switched, the working memory data can be interpreted as experiencing the low interactive condition at least once was sufficient to result in lower working memory performance, even when a high interactive task was completed in-between. Yet, performance on the subsequent high interactive task was not affected. This finding further corroborates the possibility that the difficulty of the CNP in the low interactivity condition temporarily burdens working memory performance and suggests that achieving insight in the high interactivity condition is less taxing in executive control resources (e.g., Vallée-Tourangeau et al., 2016a). This was not observed when there was a two-week time break in-between initial and subsequent efforts in Experiment 2, suggesting that the burden on working memory was temporary. This finding was not anticipated and invites further investigation. I will return to this point later in this Chapter.

Working memory was implicated for successful completion of the CNP across the four experiments and was influenced by interactivity. To explore the extent to which working memory was associated with insight across the four experiments, standardised working memory z-scores were computed for each participant. Figure 7.1 describes the average performance at Time 2 and CNP-V2 across experiments as a function of interactivity level and working memory level (based on a median split of the z-scores).

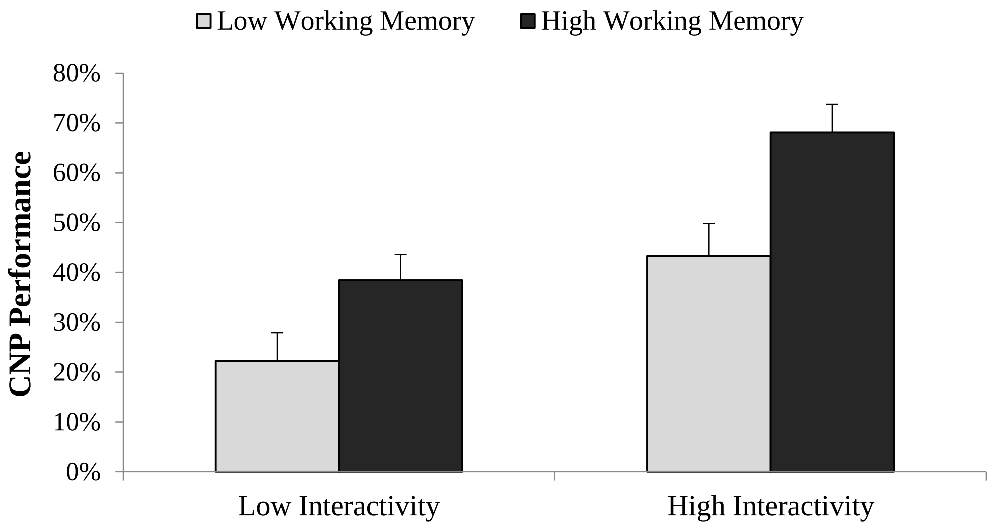

Figure 7.1. A bar graph displaying the CNP performance at Time 2 or CNP-V2 grouped by the level of interactivity and a median split for working memory z-scores.

A logistic regression analysis was conducted with the working memory z-score and the level of interactivity at Time 2 or CNP-V2 as predictors and CNP performance at Time 2 or CNP-V2 as the outcome. The regression analysis indicated that across all four experiments, the level of interactivity was a significant predictor of performance, $b = .51$, $SE = .13$, $p < .001$, as was working memory, $b = .32$, $SE = .13$, $p = .013$. However, there was no interaction between the level of interactivity and working memory on insight performance, $b = .14$, $SE = .13$, $p = .280$. As Figure 7.1 indicates, while working memory and interactivity can both contribute to insight, higher working memory capacity helps all participants do better regardless of the level of interactivity of the task. However, overall, participants are more likely to achieve insight when they can actively interact with the task materials. Internal resources are important but so is cognitive interactivity.

The additional individual differences measured in Experiments 3 and 4 were mostly unrelated to CNP performance. Participants' ability to override an intuitive response (cognitive reflection test, CRT), impulsiveness (BIS), numeracy and maths anxiety were explored. As such, no specific predictions were made. Impulsiveness, numeracy and maths anxiety were not associated with insight. However, the CRT scores, which measured participants' ability to override intuitive responses predicted insightful solutions in the low interactivity condition. Thus, people's working memory capacity or cognitive profiles may be a key factor in facilitating performance when seeking insight through mental effort alone. It is unlikely, however, that those randomly allocated in the high interactivity were just more cognitively able or more capable to find the correct solution.

Insightful performance in the high interactivity condition is better explained through the lens of the extended mind thesis, distributed cognition and the systemic thinking model. When given the opportunity to attempt the CNP in an environment that affords high levels of interactivity, insight was more frequently achieved. Increasing the degree of interactivity permits engagement of various physical and cognitive processes. The metal chains afford a richer task representation, encouraging the development of unplanned movements and interactions. Insight is enhanced by the physical restructuring of the problem presentation, not mental restructuring alone (Vallée-Tourangeau, 2014). Enacting solution attempts directly on the metal chains produces insightful solutions resulting from both deductive processing of mental representations of the task elements and inductive processing of the material presentation of those elements (Vallée-Tourangeau & Vallée-Tourangeau, 2017). Insightful solutions arise from the interactive activation of both mental restructuring and physical restructuring. Problems are solved by perceiving opportunities and being aware of the effect of current actions (Fioratou & Cowley, 2009).

The behavioural analyses further demonstrate why interactivity matters: Interactions with the chains reconfigure the problem space, enabling new strategies to emerge in a way that is not possible in a paper-and-pencil problem. The first move analysis found the initial move, be it incorrectly joining the ends of the chains together or correctly opening a middle link, did not determine performance. The initial interaction with the metal chains did not matter. Instead, the continued interactions through repeated changes of the material presentation mattered. The comparative behaviour analysis showed those who spent the largest proportion of their time projecting without acting upon the metal links failed to successfully complete the CNP. This could be explained by a failure to reach problem realisation or effectively move away from the impasse associated with the problem. By contrast, participants who solved the CNP physically restructured the presentation often, until a solution emerged. Thus, solvers in the CNP are not more insightful because they start better; they are more insightful because they overcome their first move bias through changing the physical presentation of the problem more often.

It is not possible to determine if the restructuring of the problem was a creation of thought (i.e., we see or hear, think, then act) or the recreations altered perceptions of the problem (i.e., we see or hear, act, then think). In all likelihood, the cognitive trajectory involved a succession of both planned actions (through a deductive processing loop) and unplanned actions (through an inductive processing loop). As such, interactivity and the perceptions associated with the reconstructions of the problem may be indivisible. The interplay of the action-perception cycle observed among participants shaped their solution trajectory. In the case of P127, the detailed CEA revealed an action-perception cycle was observed through the move-pause-move strategy. This suggests that changing the task environment anchors perceptions, allowing for new pathways that may not have been considered through just a deductive processing loop. Once P127 realised that joining the ends of the chains led to inevitable failure, creative solutions were sought through random chain formations. This could be interpreted as engagement in an inductive processing loop. Through these interactions, a simple miscalculation transitioned her trajectory making it possible for a solution to later emerge. Consequently, the construction, albeit serendipitous, and assessment of the constructions together helped P127 complete the CNP.

Systemic Insight: Extended Mind, Distributed Cognition and Systemic Thinking Model

The historic perspective of cognition presented in the early chapters of this thesis laid the foundation for research exploring how we come to know, understand and solve problems. According to the early Gestalts, insight is a sudden awareness of knowing what to do having been previously bewildered: The ‘Aha!’ or ‘Eureka’ experience (Mayer, 1995). Following the advent of the study of insight problem solving, theories of how and why we are able to gain insight and solve insight problems rapidly emerged. The internal and computational models of cognition (e.g., Newell & Simon, 1972; Newell et al., 1958; Simon, 1996) contribute a fragmented interpretation of information-processing (see Chapter 3, p. 52). These early accounts fail to recognise the central role the environment and our interactions with the objects in our environment may play in cognitive processing. Systemic cognition frameworks, such as the extended mind thesis (Clark & Chalmers, 1998), distributed cognition (Hollan et al., 2000; Hutchins, 1995) and the systemic thinking model (Vallée-Tourangeau et al., 2015; Vallée-Tourangeau & Vallée-Tourangeau, 2017) propose instead that information-processing activity arises, in part, from interactions with the world. As previously described, in the same manner that a blind man’s cane provides an experience otherwise impossible without his tool, interacting with tools modifies the way we think and perceive: The tools become engrossed into the neural representation of our body (Theiner, 2013). Thus, tools afford possibilities beyond the brain’s capability.

The CNP is a traditionally difficult insight problem with successful completion often less than 10% (Chu et al., 2007; Fioratou & Cowley, 2009; Fioratou et al., 2010). The counterintuitive solution to deconstruct a chain when making a necklace often results in problem solvers getting stuck. MacGregor et al. (2001, p. 192) ask “(a) How does the impasse arise? (b) How is the impasse breached?” In the CNP, the apparently easy description of the problem unfavourably affects most problem solvers. They see four chains that need to be joined together and have 15¢. The seemingly basic arithmetic instructions may prompt a solver to attempt the solution through incorrect deductions. They attempt to join the ends of two chains making maximum progress with minimum costs, half the necklace using a third of the budget. Next, they add another chain, creating a third of the necklace. Again, they add the final chain before they realise there is a long chain, but no necklace. The apparently easy problem suddenly becomes difficult. Problem solvers reach an impasse.

The difficulty may rest with the representation of the chains as tight perceptual links, which is perceiving the problem as just four chains ignorant to the individual links constructing the chains. Specifically, according to the representational change theory (RCT), problem solvers focus on the chains instead of the links (Öllinger et al., 2013). According to RCT, problem solvers ought to create new mental representations of the problem in order to achieve insight. Contrastingly, the criterion for satisfactory progress theory (CSPT) assumes that problem solvers become stuck on the incorrect first move, which makes the most apparent progress towards the goal. Consequently, many problem solvers reach an impasse due to self-imposed constraints hindering solutions (Ohlsson, 2011; MacGregor et al., 2001). Constraints are relaxed based on the breadth of the problem representation and the constraint applied (Ormerod & MacGregor, 2017). However, some constraints are more difficult to relax than others (Knoblich, Ohlsson, & Raney, 2001). For example, in the Matchstick algebra problems, the Type D arithmetic expressions constraints are more difficult to relax than the Type A constraints (Knoblich et al., 1999; Weller et al., 2011).

In the view of the systemic thinking model, impasse arises when a problem solver has exhausted her cognitive efforts through the deductive processing loop. As observed in the CEA of P127, once she realises that her planned guided actions have failed, she reaches an impasse. Across all four experiments, most naïve participants fail to break their impasse and were unable to find the solution to the CNP in both the low interactivity and high interactivity conditions. While substantially more participants in the high interactivity condition produced the insightful solution, interactivity alone was not always enough to break the impasse. This may be explained by naïve participants finding it difficult to relax their self-imposed constraints even when enacting their solution.

Interacting with the metal chains facilitated insight greatly. As observed in the CEA of P127, the impasse was breached when she let go of what she thought she should do. Instead of planning actions and the next step through a deductive processing loop, evident through her repetition of failing strategies, she explores and makes unplanned explorations. She created changes to the problem presentation and then seemingly assessed the usefulness of those changes. The sequence move-pause-move suggests an engagement in an inductive processing loop. After the impasse is breached, she was able to successfully produce and reproduce the suitable solution for the CNP. For many problem solvers in the four experiments, the impasse is breached through restructuring incorrect perceptions and constraints following an incubation period. In other words, both interactivity and incubation are able to successfully break the impasse. The two-week break considerably enriched insightful solutions at Time 2 (Experiments 1 and 2), with the disruption to problem solving while completing cognitive reflection and impulsivity tests conceivably promoting performance increases during CNP-V2 (Experiments 3 and 4). Those most likely to overcome their impasse were those who worked on a richer representation of the problem at Time 2 or CNP-V2 than in their initial solution attempt (Experiments 2 and 4). The incubation effect, however, was impeded when interactivity levels were reduced from a high interactivity level to a low interactivity level. Incubation effects that breach the impasse were affected by the level of interactivity afforded. This suggests that restructuring is not solely a mental process. Providing the opportunity to process information through both a deductive processing loop and an inductive processing loop by creating an interactive task environment alters perception, playing an important function in the enactment of insight.

To raise Wertheimer's (1959, quoted in Mayer, 1995, p. 3) question once more, "Why is it that some people, when they are faced with problems, get clever ideas, make new inventions and discoveries? What happens, what are the processes that lead to such solutions?" Some may account solutions as business-as-usual reproductions of pre-existing knowledge (e.g., Bowden et al., 2005). Specifically, MacGregor et al. (2001) CSPT would explain participants' attempt to achieve the maximum amount of apparent progress with each move, accomplished by what the problem solver thinks they already know about the problem. By contrast, Ohlsson (1992, 2011) RCT could assert problem solvers ought to create new mental representations of the problem in order to achieve insight through a special-process. More recently, Fleck and Weisberg (2013) would argue that these positions are not mutually exclusive. Both contribute to the processes that lead to insightful solutions. Although the findings in this thesis cannot determine whether insight is sudden and unexpected, or if we use a simple process of analysis, most participants were observed to begin their CNP problem-solving trajectory by joining together the ends of the chains. Accordingly, participants begin by using a business-as-usual process of thinking to find a solution. The instructions informed problem solvers they are required to make a necklace; hence it is unsurprising that most start by making a 6-link chain. When problem solvers realised that this solution is not possible, they reach an impasse. Some problem solvers were even observed to retry the same failing maximising strategy repeatedly, such as P127. Eventually, the participants neglect productive thinking, which is trying to find a solution based on their pre-existing knowledge. Instead, they explore new possibilities to gain new insight. This is typically done through restructuring, a special-process to break the impasse. As such, a continuum of business-as-usual and a special-process may better explain the cognitive process underlying insight in the CNP (Fleck & Weisberg, 2004, 2013). However, the integrated theory of insight is grounded in belief that insight occurs purely from mental effort and restructuring (Fleck & Weisberg, 2013).

Insightful solutions to the CNP were expedited when problem solvers interacted with the metal chains. The business-as-usual, special-process and integrated theory describe the insight processes indifferent to the agent-situated environment. While the findings in this thesis align closer with integrated theory of insight (Fleck & Weisberg, 2013), how the restructuring that ultimately breaks the impasses occurs is better explained in light of systemic cognition. Insight is enhanced by the physical restructuring of the problem presentation, not mental restructuring alone (Vallée-Tourangeau, 2014). Enacting solution attempts directly on the metal chains produces insightful solutions resulting from both deductive processing of mental representations and inductive processing (Vallée-Tourangeau & Vallée-Tourangeau, 2017). Accordingly, insightful solutions are a spread of the interactive activation of both mental restructuring and physical restructuring. In other words, the CSPT, RCT and integrated theory of insight are limited to describing the insight process when problem solvers are restricted to solving problems in a low interactive paper-and-pencil task environment. If the insight process is assumed to be a window into how we know, understand and how we solve problems in day-to-day life, the theories offer a partial interpretation. The insight process in historic and current literature is not representative of thinking in the world, or 'cognition in the wild'. Sultan, Köhler's insightful chimpanzee, is unlikely to have contemplated to join sticks together to get his banana. Sultan's search around the room and random interactions with objects in which he perceived their possibilities is more likely an explanation of his problem solving. The interdependent nature of action and thinking expressed by the systemic thinking model provides a more representative account of the insight process.

Methodological Observations and Future Directions

The experiments presented in this thesis examined the interplay between interactivity, incubation and transfer in insight problem solving performance. In order to do so, it was essential to design experiments that employed traditional cognitive psychology methodology while varying the degree of interactions afforded by the environment and exploring problem solving more representative of our everyday experiences. As such, in Experiments 1 and 2 a prolonged incubation period spanning over weeks was used, which was more representative of the type of real-world incubation often anecdotally described (e.g., Poincaré, 1921). However, some participants failed to return for the second trial of participation. In Experiment 1, of the 11 participants who didn't return for the second session, five participants were in the low interactivity condition and six were in the high interactivity condition. One of the participants in the low interactivity condition successfully completed the CNP and four out of the six participants in the high interactivity condition completed the CNP.

It is not possible to explain this unanticipated methodological limitation: There is little difference between the level of interactivity participants attempted the CNP with or whether participants failed their initial attempt. Thus, it remains unclear why some participants didn't return for the second session. To prevent losing participants, in Experiments 3 and 4, participants were only tested in a single session and were given filler tasks, specifically the BIS-11 impulsiveness scale and the cognitive reflection test to complete during CNP versions. The results when participants were tested in a single session presented a similar trend to when they were given a two-week break. Thus, it is unlikely that failure to return for the second session was implicated in overall solution rates. Nevertheless, it is an important note for future research that requires multiple stages of participation in which some participants may simply cease to continue participation.

The working memory data revealed some unexpected findings; insightful solutions achieved in the high interactivity condition are less taxing on executive control resources. There are two views that the data can support. Firstly, that working memory capacity for those in the high interactivity condition was simply higher than those in the low, despite random allocation to conditions. Alternatively, and more likely, it is possible that working on the difficult problem followed by a difficult working memory test is like doing “mental gymnastics” (Chemero, 2009, p. 43). Efforts to complete the CNP placed large cognitive demands in the low interactive condition, which depleted subsequently working memory performance. The CNP presumably temporarily fatigued participants’ ability to execute executive functions, a state of ego-depletion (Inzlicht & Schmeichel, 2012). No firm conclusion can be drawn from the present work as working memory was only measured once after both attempts of the CNP. To better explore whether working memory capacity is more important under low interactivity, it would be interesting to experimentally burden executive functions first and observe the impact of this manipulation on insight performance. If indeed working memory is more important when opportunities to interact are low, constraining working memory resources should negatively impact insight performance under low interactivity levels but not under high interactivity levels.

Another important question that invites further examination is the role of metacognition and self-regulation when solutions are derived from deductive mental processing. The CRT scores, which measured participants’ ability to override the natural instinct and be more deliberative in their thinking (Frederick, 2005), was important for predicting insight in the low interactive condition only. This finding suggests that participants who were more likely to suppress their heuristic intuitive answer when completing the CRT were also more likely to achieve insight in the CNP. In other words, those successful participants were better at correcting the intuitive path to solution, which consists of connecting the end of each chain. This unanticipated association between CRT scores and insightful solutions is possibly explained by two key drivers of goal-oriented thinking; *metacognition*, awareness of their own thinking to guide and improve efficiency (Davidson, Deuser, & Sternberg, 1994), and *self-regulation*, dynamic efforts employed by individuals to monitor and change behaviours and cognition (Carver & Scheier, 2000).

Future research could thus explore; (i) insight performance when executive controls are diminished and (ii) the impact of interactivity levels on cognitive load. Prospective participants would begin by completing a working memory test, such as the BD-Span, to get a measure of their baseline working memory score. Subsequently, they would perform a taxing and ego-depleting task, such as the *letter-e task* (Hagger, Wood, Stiff, & Chatzisarantis, 2010). The letter-e task requires people to identify words containing a lonely letter-e, where the letter-e must be at least two letters away from the nearest vowel. For example, ‘**o**ff**e**nds’ contains a lonely letter-e but b**u**s**i**n**e**ss does not. The ability to correctly identify lonely letter-e’s reduces over time, demonstrating diminished executive functioning (Arber, Ireland, Feger, Marrington, Tehan, & Tehan, 2017). The letter-e task is effective in temporarily burdening working memory and will diminish self-regulation. After completing the letter-e task, participants would complete the CNP in either a low interactivity condition or a high interactivity condition.

Participants could also be established as having either a high or low executive control, based on the initial working memory score. The allocation of task environment would not be as random as in the experiments in this thesis. Instead, they will be evenly distributed into interactivity conditions. For example, the research design could be a 2 (low executive control, high executive control) × 2 (low interactivity, high interactivity) between subject design, to help establish whether working memory is mitigated in a high interactive task environment. Following the CNP attempt, a second BD-Span measure to assess the decline in executive controls. It could be predicted that CNP performance in the high interactivity condition would remain significantly higher as a function of the task environment mitigating the need for internal cognitive resources. As such, there will be little difference between those who score as low executive control and high executive control when completing the CNP in a high interactivity condition. By contrast, having better executive functions will help gain insight when using deductive processing in the low interactivity condition.

The behavioural observations and analyses of interactions with the metal chains disclosed an abundant data source to evaluate and detail insight problem solving in highly interactive task environments. The first move analysis established that the first move is not as important as the CSPT assumes. Problem solvers are no less likely to find the solution if they begin by maximising, which is incorrectly joining together the ends of the chains. The comparative behavioural analysis discovered altering the perceptual layout of the problem presentation facilitated insight, which supports Vallée-Tourangeau et al. (2015) findings with Bayesian reasoning problems. The idiographic cognitive event analysis detailed the problem-solving trajectory of P127, pinpointing the exact event that determined her insight. Nonetheless, these findings only scratch the surface in explaining why interactivity matters. It is not possible to infer the participants' decision-making associated with each interaction.

Studies exploring the CNP have often used verbal protocols to try to understand the problem-solving trajectories (e.g., Silveira, 1971; Metcalfe & Wiebe, 1987). Although the think-aloud protocol is typically used to determine the insight process (Fleck & Weisberg, 2013; Weisberg, 1995; Metcalfe, 1981), it was not used in the experiments to avoid any potential interference with the insight experience. The systemic thinking model predicts interacting with the metal chains in the high interactivity version of the CNP allows behaviour and action to be understood not solely as the result of deductive processing of mental representations, but as a mix of deductive and inductive processing (Vallée-

Tourangeau & Vallée-Tourangeau, 2017). The participants in the four experiments were given the opportunity to engage in an inductive loop, in which the unguided and unplanned actions facilitated insightful solutions. Asking the participants to solve the CNP while thinking all of their thoughts out loud could have forced them to artificially engage exclusively in a deductive processing loop, where interactions would become guided and planned. Consequently, one would expect that verbal protocols would constrain opportunistic insightful solutions emerging from unguided and unplanned interactions.

Future research may test these predictions of the systemic thinking model more directly. A narration of participants thinking could provide more perceptive as to why certain actions were performed by participants. Specifically, to better establish why interactivity help participants, an observation of high interactivity conditions where participants are invited to use verbal protocols could explore this. In the view that verbal protocols may force participants to artificially engage in a deductive processing loop, an alternative can be to interview participants after they complete the CNP to ascertain their insight process.

The metal chains afforded high interactivity participants a richer external representation of the CNP from which they could engage in both deductive and inductive processing. The choice to use the metal links was substantiated in previous CNP research that suggested they were an operative physical representation of the problem (e.g., Fioratou & Cowley, 2009). Nevertheless, it is possible that a physical representation from a different material may have had a different impact upon performance. In the 17A experiments by Vallée-Tourangeau et al. (2016b), although participants completed the same problem, the different tools used across experiments to construct their solution had an impact on insightful solution rates. Specifically, those who were provided with metal hoops in Experiment 2 solved the problem substantially more often than those using straight pipe cleaners in Experiment 1. This difference in performance was explained by Vallée-Tourangeau et al. as participants being more familiar with overlapping circles (e.g. Audi sign and the Olympic rings) and overlapping animal pens were a key feature of the insightful solution in the 17A task.

It would be interesting to explore the possibility of problem solvers using a different physical representation other than metal links to construct the solution to the CNP. Further, to explore the impact on insight performance when participants are required to innovate their problem-solving tool (i.e., creating the animal pens in the 17A task from the pipe cleaners) or use available tools (i.e., using premade animal pens from metal hoops in the 17A task). Tool innovation, which is the discovery, creation and performance of novel information, is more difficult than using tools already created, since innovation underpins more complex cognitive mechanisms (Vaesen, 2012). Development research has shown that while children easily use pre-made tools during ill-structured problem solving, they struggle to use tools in an innovative manner (Beck, Apperly, Chappell, Guthrie, & Cutting, 2011). To explore the distinction between tool use and tool innovation, Beck et al. (2011, Experiment 1) asked children to retrieve a sticker out of a tube too narrow to reach into with their hands. The sticker was designed with a handle so it could be retrieved with a hook. A bent pipe cleaner made to look like a hook (tool use) and a straight pipe cleaner (tool innovation) were placed near the bucket. The children could use either to retrieve the sticker. Significantly more children opted for the bent pipe cleaner demonstrating they would rather use a tool than innovate one. In a second experiment where children were only provided with a straight pipe cleaner and two short matchsticks, tool innovation was remarkably difficult for children under 5 years old. The majority of children who retrieved the sticker created a hook by bending the pipe cleaner, while some children used a matchstick to create an inverted T shape. Effective tool use and tool innovation are distinct features of human cognition (Vaesen, 2012).

This raises the question as to whether participants in the high interactivity condition in the CNP performed better because the metal chains were representative and easy to use. To explore the distinction between tool use and tool innovation when completing the CNP in a high interactive task environment, the materiality and affordance availability could be altered. To do so, problem solvers could be asked to make the structure of the problem prior to attempting to solve it similar to Weller et al. (2011) Matchstick algebra problem. It would be valuable to explore whether participants creating the chains out of single links first would still attempt to link the ends of the chains to solve the problems. Furthermore, it would be useful to explore the impact of affordances, tool use and tool innovation in a different problem that did not have such a clearly defined goal state, such as the 17A problem. For example, participants could be given both the pipe cleaners and the metal rings to create the animal pens. When the goal state is ill-defined, participants' selection of the straight pipe cleaners (tool innovation) and metal hoops (tool use) as problem-solving tools could provide a wealth of information of the role of affordance and cognitive interactivity.

Concluding Remarks

Across the experiments, the rich external resources afforded by the metal chains greatly increased insightful solutions. Although participants' working memory and cognitive reflectivity were associated with insight, this was mostly important for participants engaged in a low interactivity paper-and-pencil condition. In other words, the increased insightful solutions in the high interactivity condition were not contingent solely on the person completing the task; it was contingent on both the person and the environment the task was completed in. The problem space, which is what the solver comprehends as the path to solution based on the initial state and the goal (Newell & Simon, 1972) is extended beyond intelligent information-processing when interacting with the metal chains. While computer programmes, such as the logic theorist, are alleged to emulate human cognition to generate solutions based on the computational capacity of intelligent information-processing systems (Newell et al., 1958), computers cannot imitate the coordination between the agent and the environment (Hutchins, 1995). Information-processing occurs beyond a mental representation of the CNP, guided by the dynamic high interactive task environment to govern insight and, more broadly cognition (Clark, 2008). Readdressing Newell and Simon (1976) comment:

> Intelligent action is everywhere around us in the biological world, mostly in human behaviour. It is a form of behaviour we can recognize by its effect whether it is performed by humans or not. The [physical symbol system] hypothesis could indeed be false. Intelligent behaviour is not so easy to produce that any system will exhibit it willy nilly. Indeed, there are people whose analyses lead them to conclude, either on philosophical or on scientific grounds, that the hypothesis is false. Scientifically, one can attack or defend it only by bringing forth empirical evidence about the natural world. (p. 87 – 88)

The empirical evidence across the four experiments demonstrated naïve participants in the high interactivity condition produced the correct, insightful solution more frequently than those in the low interactivity condition. Hence, it was distinctive that increasing the level of interactivity afforded by the metal chains caused better performance in the CNP. The behavioural observations and analyses instigated an explanation for how and why interactivity matters. Spending the largest proportion of allotted time altering and restructuring the physical presentation of the problem leads to insightful solutions. As observed in the CEA of P127, the events that led up to her successfully completing the problem can be interpreted as engagement of both a deductive processing loop and an inductive processing loop. Altogether, the findings presented in this thesis add to the body of evidence suggesting that information-processing amounts to more than mental processing:

Interacting with the environment matters. Internal mental representations and cognitive capacities play an important role, but are not dominant, with the findings demonstrating insight as a systemic occurrence: Embodied, enacted, embedded, extended and distributed through cognitive interactivity. As Clark (2003) puts it:

> It is the mind-body-scaffolding problem. It is the problem of understanding how human thought and reasoning is born out of looping interactions between material brains, material bodies, and complex cultural and technological environments. We create these supportive environments, but they create us too. (p. 11)

The unique results presented in this thesis contribute to show that insight through physical processing fosters stronger performance on a subsequent task, both when the task remains the same and when varies. There were two additional novel and original contributions: Firstly, an effect of incubation is mostly manifest when problem solvers work in high interactivity level when encountering the same problem (Experiment 2) or a similar problem (Experiment 4) after a break. Second, transfer is prevalent when solutions to the source problem are self-generated (Experiments 3 and 4). When transferring a solution from a one problem to another, experiencing a high interactive task environment following an incubation period allows the problem solver to think in a world they can enact in, crucially, not frequently possible in the psychologists' lab. This unique finding underscores the importance of adopting a systemic cognition perspective when exploring the incubation and transfer effects in insight problem solving.

Interactivity has a wide-reaching scope for researchers to further explore the determinants of insight. Research has established incubation and transfer enhance insight. However, the current literature on these determinates is premised on mental representations and restructuring. Insight and new discoveries can be propelled by engaging with the world around us, by utilising the tools afforded and by altering the perceptual layout of our environment until we have a breakthrough. In accordance with the systemic thinking model's unique perspective, engaging in both deductive processing and inductive processing through increasing interactivity and, by way of consequence, increasing reasoners' opportunities to process perceptual inputs plays a critical role in cognition. To conclude, the findings reported in this thesis demonstrate while incubation helps us build upon a solution, cognitive interactivity enables naïve problem solvers to find insightful solution more often. Clever ideas are not just an outcome of effortful thinking, but meaningful interactions with our environment.

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